Final Technical Report

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Development of a Pattern Recognition Methodology for Determining Operationally Optimal Heat Balance Instrumentation Calibration Schedules

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1. Introduction

In July 1999, The University of Cincinnati, Argonne National Laboratory and First Energy's Davis Besse Nuclear Power Station [DBNPS] received DOE support under the auspices of the Nuclear Engineering Educational Research Program to develop and apply an Advanced Pattern Recognition Methodology for Determining Operationally Optimal Heat Balance Instrumentation Calibration Schedules [1]. This is the final report on the results achieved during the project period which began in July 1999 and extended to December 31, 2001.

A major problem in operating complex systems is ensuring that all parameters are within their allowed range. One solution to this problem is to establish a list of major parameter values, with appropriate upper and lower limits for each mode of operation or for each state of the plant. These parameters are examined regularly and checked against their limits in a process referred to as a polling technique. Often, important parameters will have alarm annunciators to indicate violation of these limits. Some of the difficulties with this approach are that it is not very accurate in the dynamic sense and usually cannot detect the onset of slow decalibration drifts [5].

The goal of the project is to enable plant operators to detect with high sensitivity and reliability the onset of decalibration drifts in all of the instrumentation used as input to the reactor heat balance calculations. To achieve this objective, the collaborators developed and implemented at DBNPS an extension of the Multivariate State Estimation Technique (MSET) pattern recognition methodology pioneered by ANL [2]. The extension was implemented during the second phase of the project and fully achieved the project goal.

The Multivariate State Estimation Technique (MSET) is a software system for real-time process monitoring. It provides system operators with timely and reliable information regarding the conformance of process behavior, as inferred from sensor readings, with the expected behavior based on past observation. MSET employs highly effective, patented techniques to: (1) generate an analytical estimate of sensor signals on the basis of actual sensor readings and previously learned correlations among them, and (2) analyze the statistical characteristics of the time series obtained by taking the difference between each measured signal and its numerically generated counterpart to determine, at the earliest possible time, whether the process is behaving as expected or anomalously.

The reliability, sensitivity and efficiency of MSET have been demonstrated for a wide variety of process monitoring, signal validation, and sensor operability surveillance applications.

2. Phase 1 Results

In preliminary discussions in July, 1999, Davis Besse Nuclear Power Plant [DBNPP] Senior Engineers {Eugene Matranga and Michael Nelson} agreed to provide DBNPP process computer data (by email) from in Excel format. This data allowed was at a sampling rate of one data point per day for a whole year [365 measurements] However due to operational problems there was really steady state data were only for about 7 months (230 days). Using the foregoing data the evolution of the power plant during the whole year was tracked to determine some steady state periods, which could be used in the model for training.

To obtain high sampling-rate data during the selected periods, it was necessary to process DBNPP process computer data from a VMS format into an MSET-input compatible format. An account was established on the VMS/VAX computer at Argonne National Laboratory and DBNPP process computer data was extracted from tapes provided by Davis Besse. The data was then successfully processed into an MSET-compatible format (ASCII, TEXT, XLS). Two different periods were chosen one from the beginning of the operating cycle the other one from the end of the operating cycle.

Then the engineers from the Davis-Besse Nuclear Power Plant also provided a list of 37 sensors, which are the most important for calculating the reactor heat balance (see **Table 2.1: The 37 sensors used to calculate the Heat Balance Transfer**).

The signals that are included in the model are those that are most highly correlated with the sensors used to calculate the Heat Balance Transfer.

The data from the VMS computer contained 251 sensors and 2880 measurements recorded during a whole day with the sampling rate of 2 measurements per minute.

Using Matlab Software the correlation coefficients were computed for all of the 251 sensors and the sum of correlation coefficient was calculated for every one. Then, using these 37 most important sensors another matrix of sensors was computed to see which sensors among all 251 were highly correlated with the 37 Heat Balance Model sensors. A more detailed description of the correlation calculations is provided in Reference 8.

The decision of relevant sensors to include in the surveillance module and the selection of supporting memory matrix columns from all the available training data are decisions that influence the overall structural uncertainty of the model so the sensors were chosen very carefully by making several tests before choosing them (Forward Selection using BART, Linear Regression, Matrix of Correlation Coefficients).

For systems with more than two variables (important sensors) SPRT uses a nonlinear multivariate regression technique that employs the Bounded Angle Ratio Tests (BART) in N-dimensional space (known in vector calculus terminology as hyperspace) to model the relationship between all of the variables. The BART is a method of measuring similarity between scalar values. BART uses the angle formed by the two points under comparison and a third reference point lying some distance perpendicular to the line formed by the two points under comparison. By using this geometric and trigonometric approach, BART is able to calculate the similarity of scalars with opposite signs, something that conventional ratio tests cannot do.

The correlation coefficients were computed for the sensors in two different periods of time (February and November) to see if the evolution was similar. They looked pretty much the same so the assumption was made that the model will work for any period of time during the operating cycle. The sensors considered to be the most important were T671 and T672 (Main Feed Water Temperature to Integrated Control System) because they have the biggest correlation coefficients relative to the other sensors.

The MSET model is based on training data that is organized in a memory matrix whose columns correspond to specific sensors [predictors of the model], and rows correspond to measurements taken at various operating states of the system.

To provide the earliest possible indication of process anomalies, MSET employs the SPRT to detect changes over time in the statistical characteristics of the residual signals. Instead of a simple threshold limit that signals a fault when the residual exceeds some threshold values, the SPRT technique performs statistical hypothesis tests on the mean and variance of the residuals [3]. These tests are conducted on the basis of user specified false-alarm and missed-alarm probabilities, allowing the user to control the likelihood of missed fault detection or false alarms.

Fault detection model, employing the Sequential Probability Ratio Test (SPRT) analyzes the residual time series obtained by subtracting each measured signal from its numerically generated counterpart. By performing statistical hypothesis tests on these residual time series, SPRT makes a determination, at the earliest possible time, of whether the process is behaving as expected or anomalously. This determination is made subject to user specified probabilities for false alarms and missed alarms.

For all the 37 sensors the columns with the correlation coefficients were grouped in a single matrix and for the last 150 sensors the frequency of appearance of the sensor tag was registered. The sensors with the highest frequency rate were eliminated because they were the least correlated with the important sensors. Three additional sensors were eliminated because the output values were too discontinuous (discrete). A model with 93 sensors was kept to be used with MSET and SPRT.

The training matrix had about 125 vectors. The estimate signals using MSET had very close values to the real signals so the estimation errors were very small (~ 0.02%). The number of false alarms was as expected for (1000 measurements less than 3 on the average). Then, a “false” signal was introduced to see if it would be detected.

The effect of very small, artificially introduced signal variations (less than 0.1%), was investigated to see if the “bad” sensors can be identified properly. The official heat balance calculation will not reflect any significant change for such small variations of the inputs, but the MSET-model will be able to detect the degraded sensor before a major perturbation occurs and other systems are affected.

To quantify the quality of model performance, both estimation accuracy (estimation results for each sensor in the model) and fault tolerance criteria (the effect of a faulted sensor on all the other sensors used in the model), was considered. The estimation accuracy is a measure of how accurately a sensor output can be estimated based on the values of the all sensors in the model. The fault tolerance is a measure of how susceptible the sensor estimates are to the failure of a sensor. For fault tolerance, the false alarm rates resulting from mean SPRT calculations were used as a measure for this criterion.

To test the sensitivity of the MSET-HBS model, a step signal with the amplitude less than 0.14% of the average of the original signal was introduced. The MSET detected the abnormality immediately and produced alarms. Similar results were observed for sensors with approximately the same standard deviation but for sensors with bigger standard deviation (noisy signals) the model detected the disturbance for a step signal with a magnitude of about 1% of the average. **Figures 2.1** and **2.2** show a **Step signal superimposed over the original signal # 74**, and the resulting Alarm **rates.**

A ramp with a small slope was introduced in the range of the signal measurements and was also detected as abnormal and the alarm was triggered as shown in **Figures 2.3** and **2.4: Ramp signal** and the **Alarm rates.**

A superimposed ramp over the original signal was introduced in the data and MSET was able to detect this anomaly also and started to trigger the alarm. **Figures 2.5** and **2.6: Superimposed ramp signal over signal # 74 and The Alarm rates**.

A constant signal in the range of the measurements was introduced. Because the signal does not act as the model expected, the alarm was triggered. The results are shown in **Figures 2.7** and **2.8: Constant signal equal to the average value of the measurements and**

the Alarm rates. In each of the foregoing cases, MSET was able to detect that the sensor output was abnormal and triggered the appropriate alarm.

All of the estimated values are very close to the actual values of the sensor outputs. The difference between MSET estimated values and real values are shown in **Figure 2.9** for sensor # 74. On the average the estimation error was 0.146 – which means that the relative error was 0.032% of the average measured value for sensor # 74.

For studying the false alarms rates when all the sensors are operating normally, both positive and negative mean SPRT tests were run using the residuals between the training data and the estimation. First half of the data were used for training and the last half of them for testing. The parameters used for the SPRT tests were: 0.001 for false alarm probability (α), 0.001 for missed alarm probability (β). There wasn't any false alarm so, it can be concluded that the SPRT algorithm performance was as expected. For studying the fault tolerance of the system, a perturbation (failure) of a positive two standard deviation step variation of the raw signal was simulated in some of the sensors in the model. As expected, SPRT detected immediately the failures in the faulted sensors for each test. The most important results for the fault tolerance tests are presented in **Figures 2.10 - 2.17** which show how the model reacts to different numbers of degraded sensors. The model was able to detect all faulted sensors using SSA operator for less than 20 sensors faulted at a time. For a model with 50 sensors faulted SSA detected only 35 but BART was able to detect all of them. There was no spill over effect observed even for the worst scenario (half of the sensors faulted). The only thing which SSA or BART were not able to detect very precisely was the end of the degradation of the sensor. There is a little bit of inertia in detecting when the failure stopped. The inertia is related to the sensor "importance" -- in other words the degree of correlation of the faulted sensor to other sensors.

The model was very robust. There was no spillover effect -- meaning that the other sensors estimates were not affected by the modified (false) data.

Table 2.1. The 35 Sensors Used to Calculate the DBNPS Heat Balance

No.	Sensor Tag	Description
1	F673	Main Feed Water 1 Compensated Flow, FY2B2
2	F674	Main Feed Water 1 Compensated Flow, FY2B1
3	F679	Main Feed Water 2 Compensated Flow, FY2A1
4	F680	Main Feed Water 2 Compensated Flow, FY2A2
5	F859	Reactor Coolant Hot Leg Total Flow, RPS CH1
6	F861	Reactor Coolant Hot Leg Total Flow, RPS CH2
7	F863	Reactor Coolant Hot Leg Total Flow, RPS CH3
8	F864	Reactor Coolant Hot Leg Total Flow, RPS CH4
9	P721	Reactor Coolant Loop 1 Hot Leg NR Press, RPS CH1
10	P722	Reactor Coolant Loop 1 Hot Leg NR Press, RPS CH2
11	P729	Reactor Coolant Loop 1 Hot Leg NR Press, RPS CH3
12	P730	Reactor Coolant Loop 1 Hot Leg NR Press, RPS CH4
13	P930	Steam Generator 1 Main Feed Water Nozzle Press
14	P931	Steam Generator 1 Out Steam Press, PT12B1
15	P932	Steam Generator 1 Out Steam Press, PT12B2
16	P935	Steam Generator 2 Main Feed Water Nozzle Press
17	P936	Steam Generator 2 Out Steam Press, PT12A1
18	P937	Steam Generator 2 Out Steam Press, PT12A2
19	T476	High Pressure Turbine IN Temp From SG 2
20	T477	High Pressure Turbine IN Temp From SG 1
21	T671	Main Feed Water Temp TO ICS, TT1-1
22	T672	Main Feed Water Temp TO ICS, TT1-2
23	T719	Reactor Coolant Loop 1 Hot Leg NR Temp RC3B1
24	T720	Reactor Coolant Loop 1 Hot Leg NR Temp RC3B3
25	T721	Reactor Coolant Loop 1 Hot Leg NR Temp RPS CH1
26	T722	Reactor Coolant Loop 1 Hot Leg NR Temp RPS CH3
27	T728	Reactor Coolant Loop 1 Hot Leg NR Temp RC3A1
28	T729	Reactor Coolant Loop 1 Hot Leg NR Temp RC3A3
29	T730	Reactor Coolant Loop 1 Hot Leg NR Temp RPS CH 2
30	T731	Reactor Coolant Loop 1 Hot Leg NR Temp RPS CH 4
31	T780	Reactor Coolant Pump 1-1 Disch Cold Leg NR Temp 1
33	T800	Reactor Coolant Pump 1-2 Disch Cold Leg NR Temp 3
33	T820	Reactor Coolant Pump 2-1 Disch Cold Leg NR Temp 1
34	T821	Reactor Coolant Pump 2-1 Disch Cold Leg NR Temp 2
35	T840	Reactor Coolant Pump 2-2 Disch Cold Leg NR Temp 3

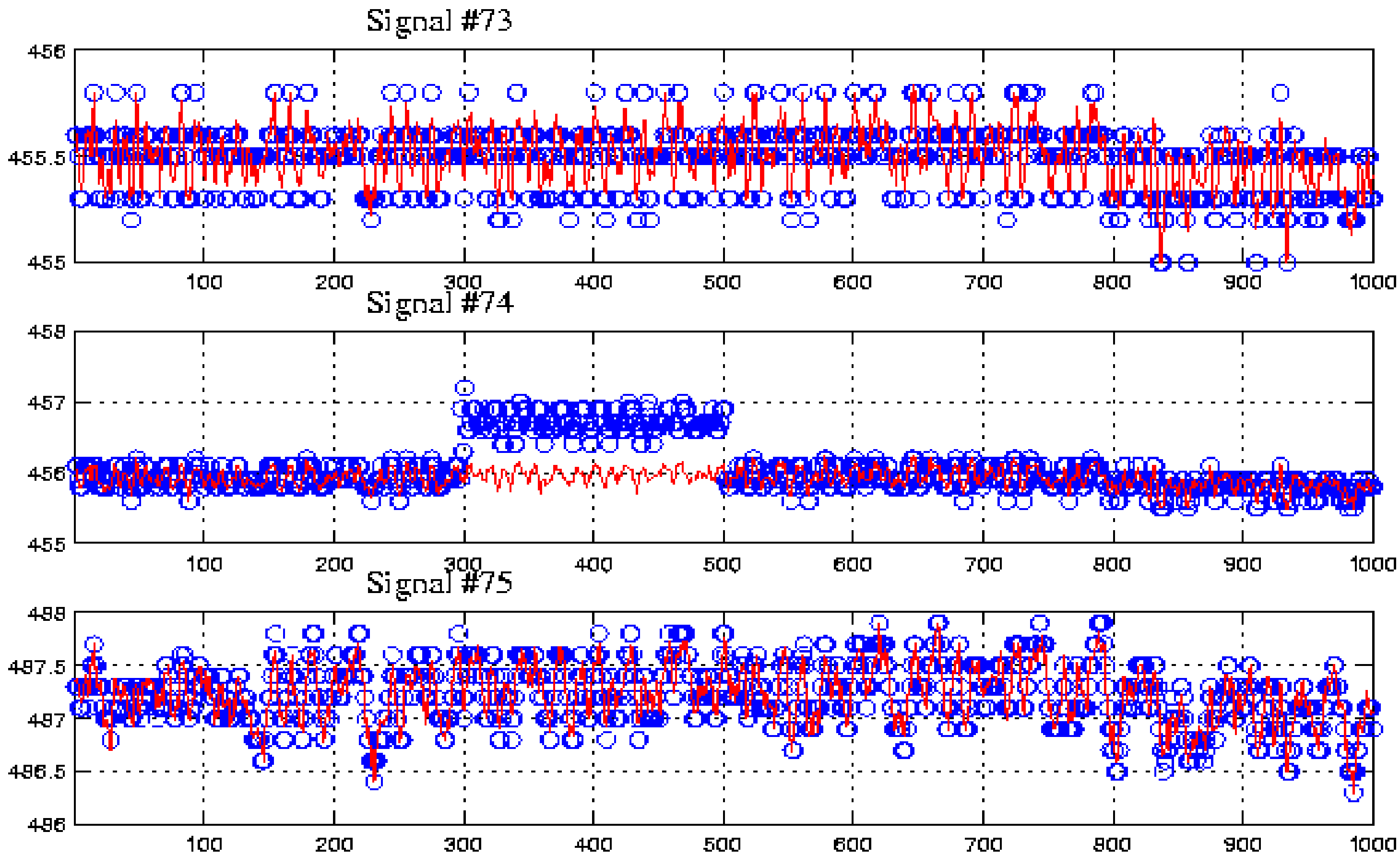


Figure 2.1: Step signal superimposed over the original signal # 74

O – Original signal, __ MSET estimate.

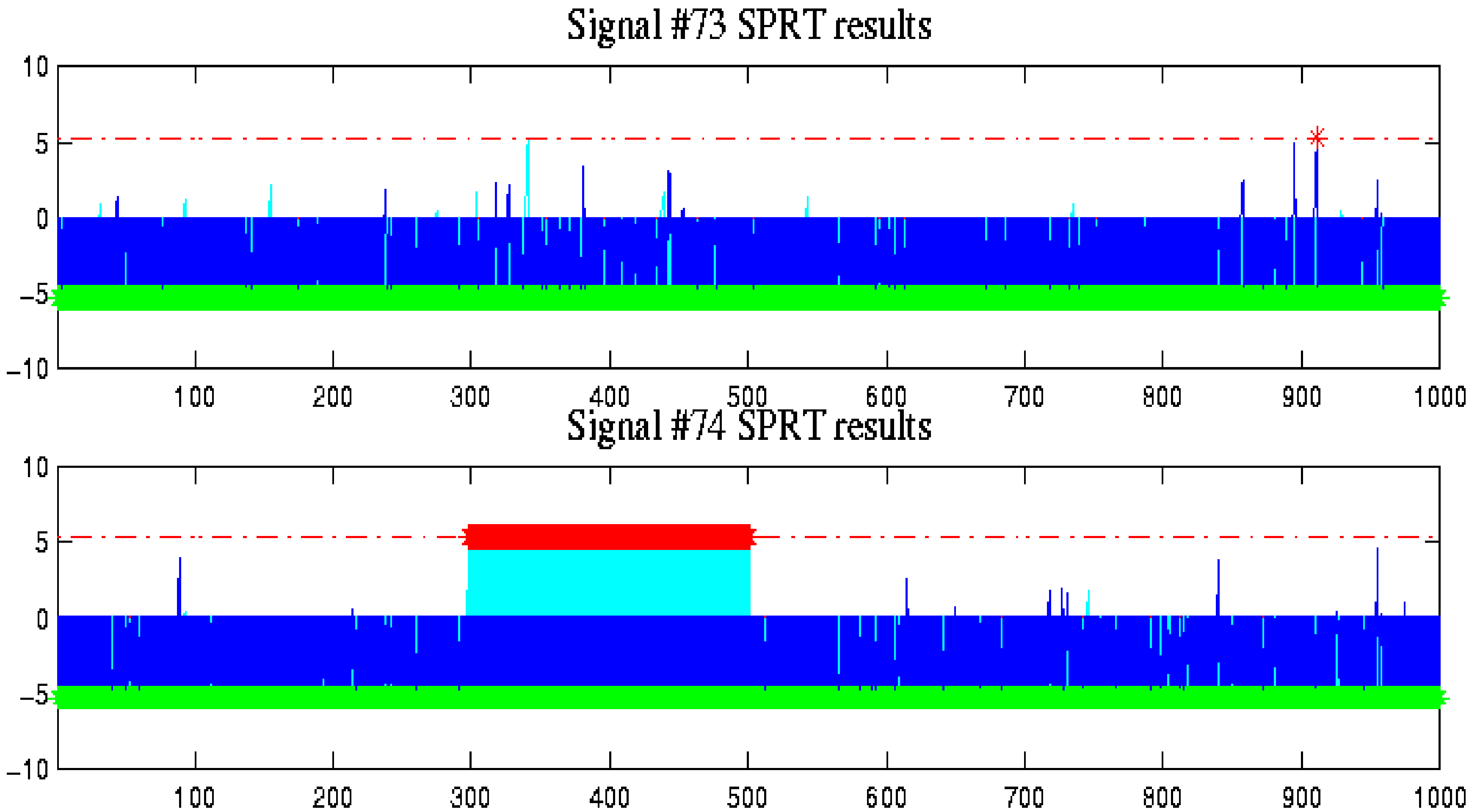


Figure 2.2: Alarm rates (Step signal superimposed over the original signal #74)

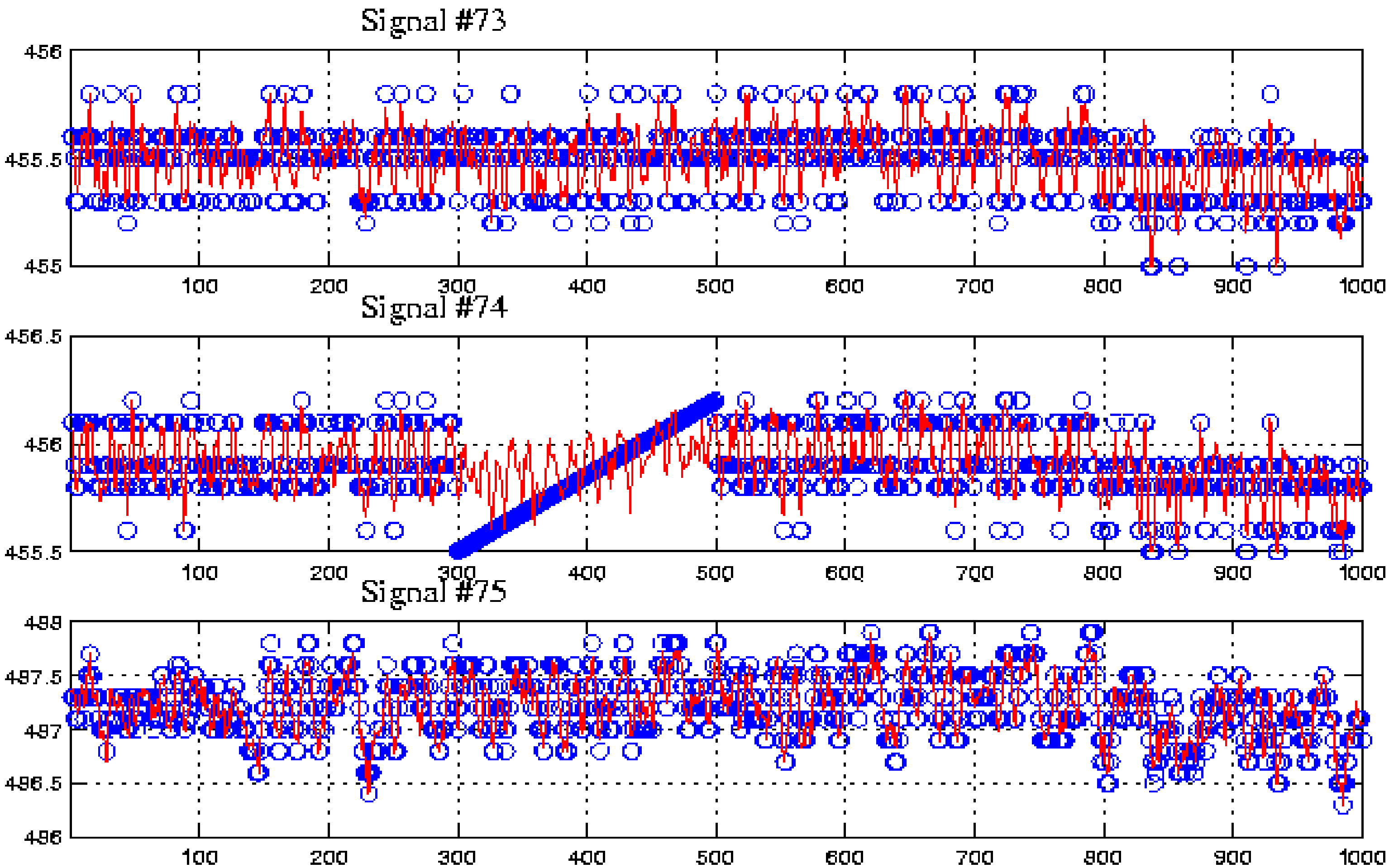


Figure 2.3: Ramp signal Deviation (from the lowest to the highest measured value of the signal #74)

O – Original signal, __ MSET estimate.

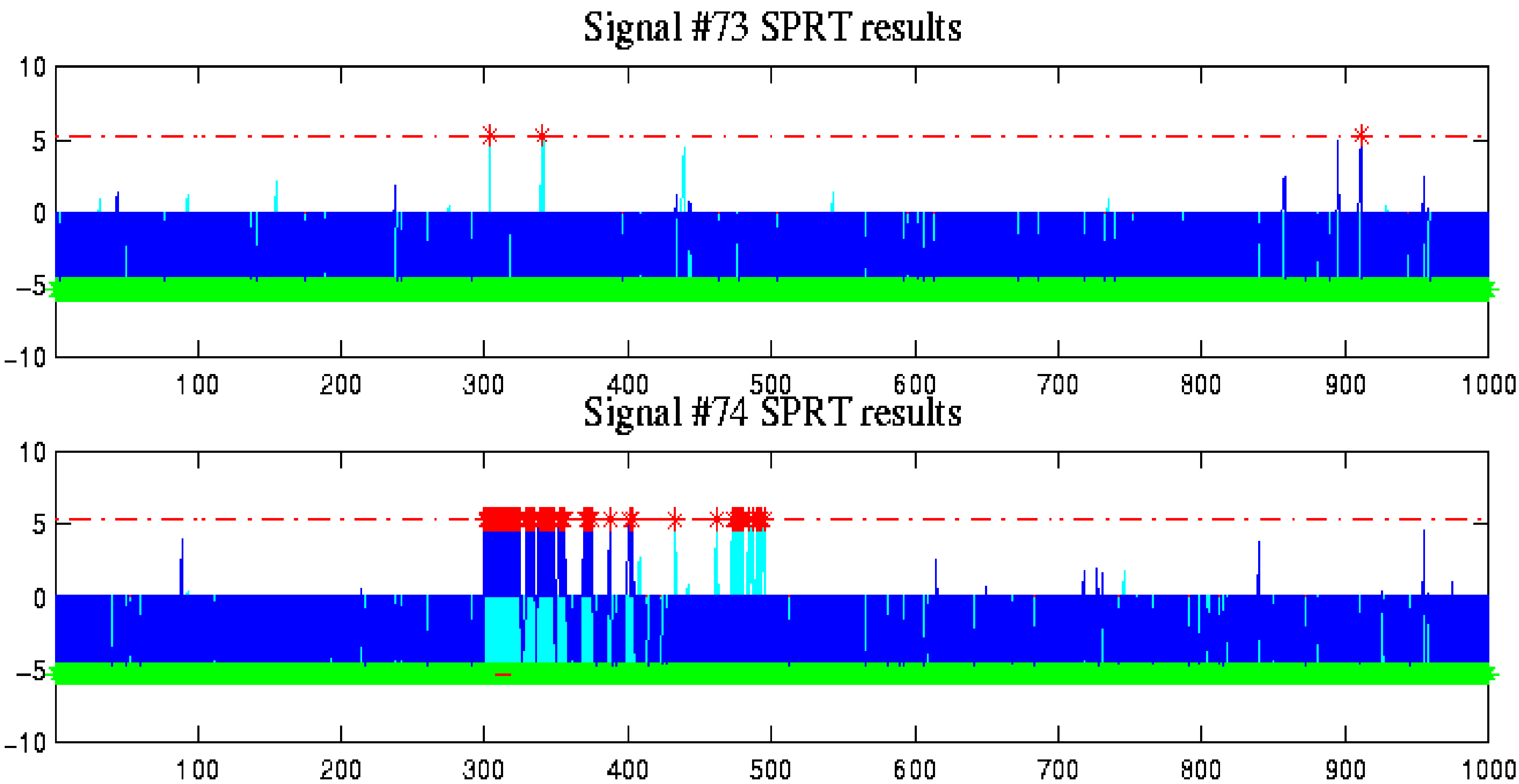


Figure 2.4: Alarm rates (for the ramp signal deviation in Figure 3)

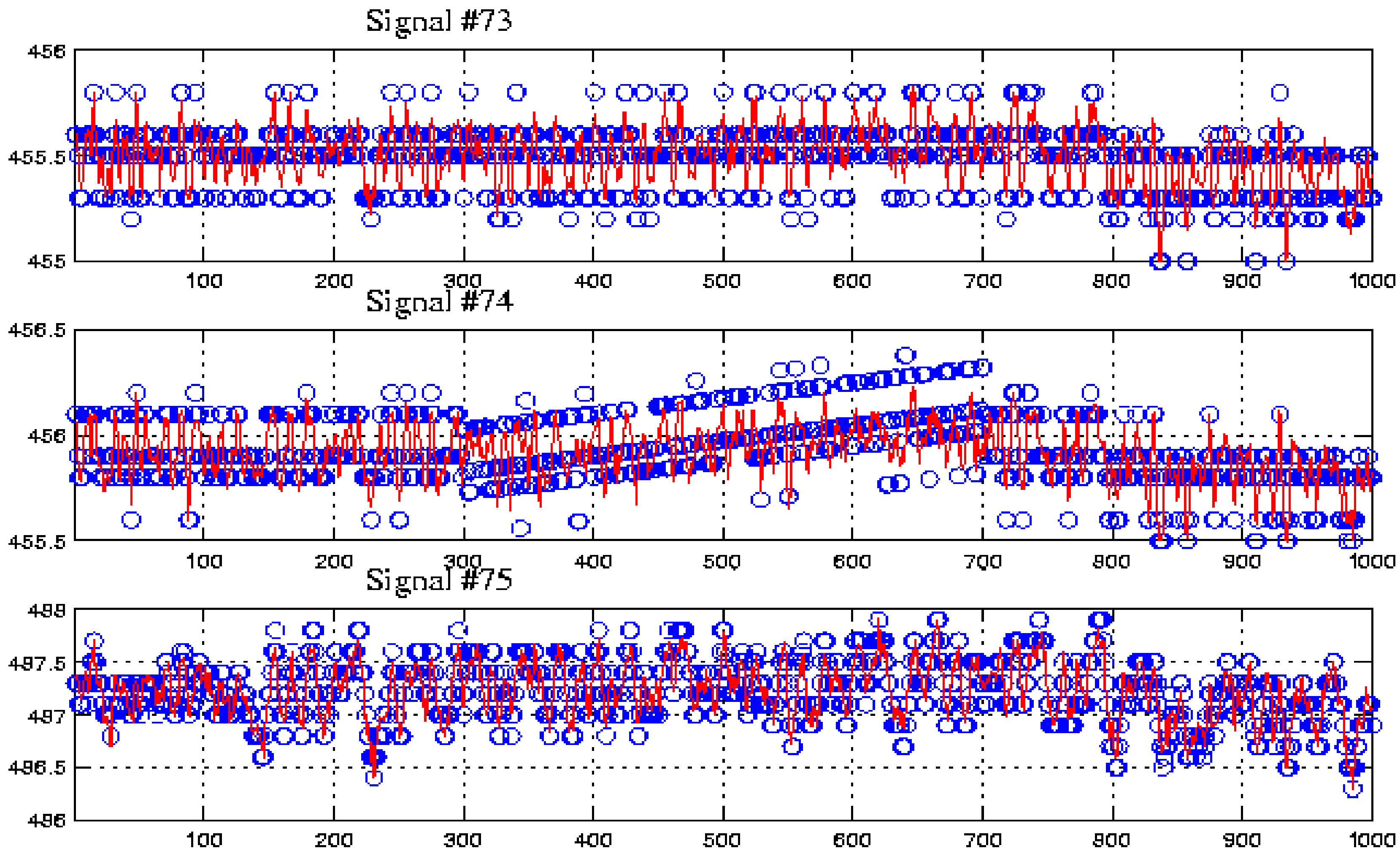


Figure 2.5: Superimposed ramp signal over signal # 74

O – Original signal, __ MSET estimate.

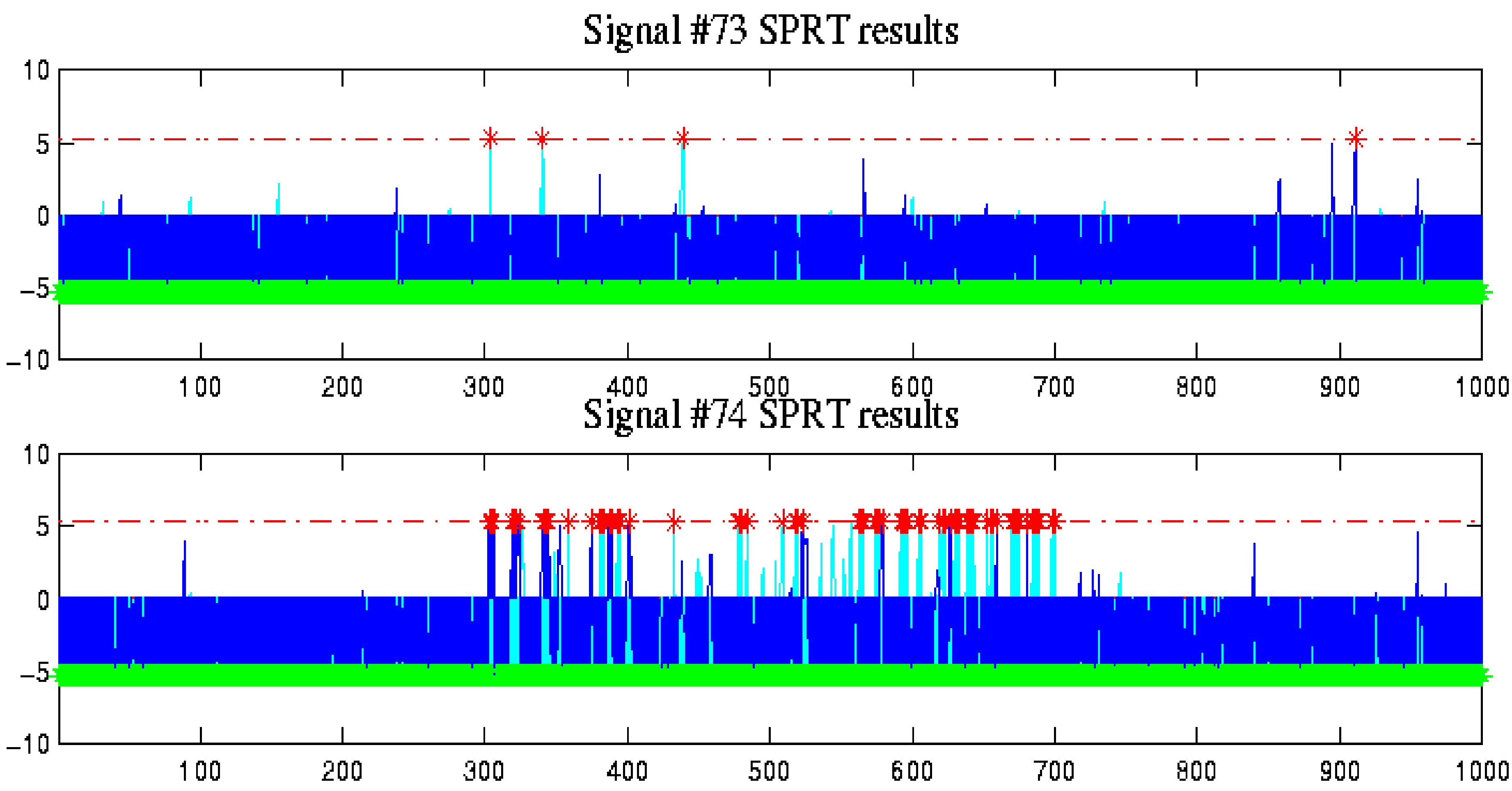


Figure 2.6: Alarm rates (Superimposed ramp signal over signal # 74)

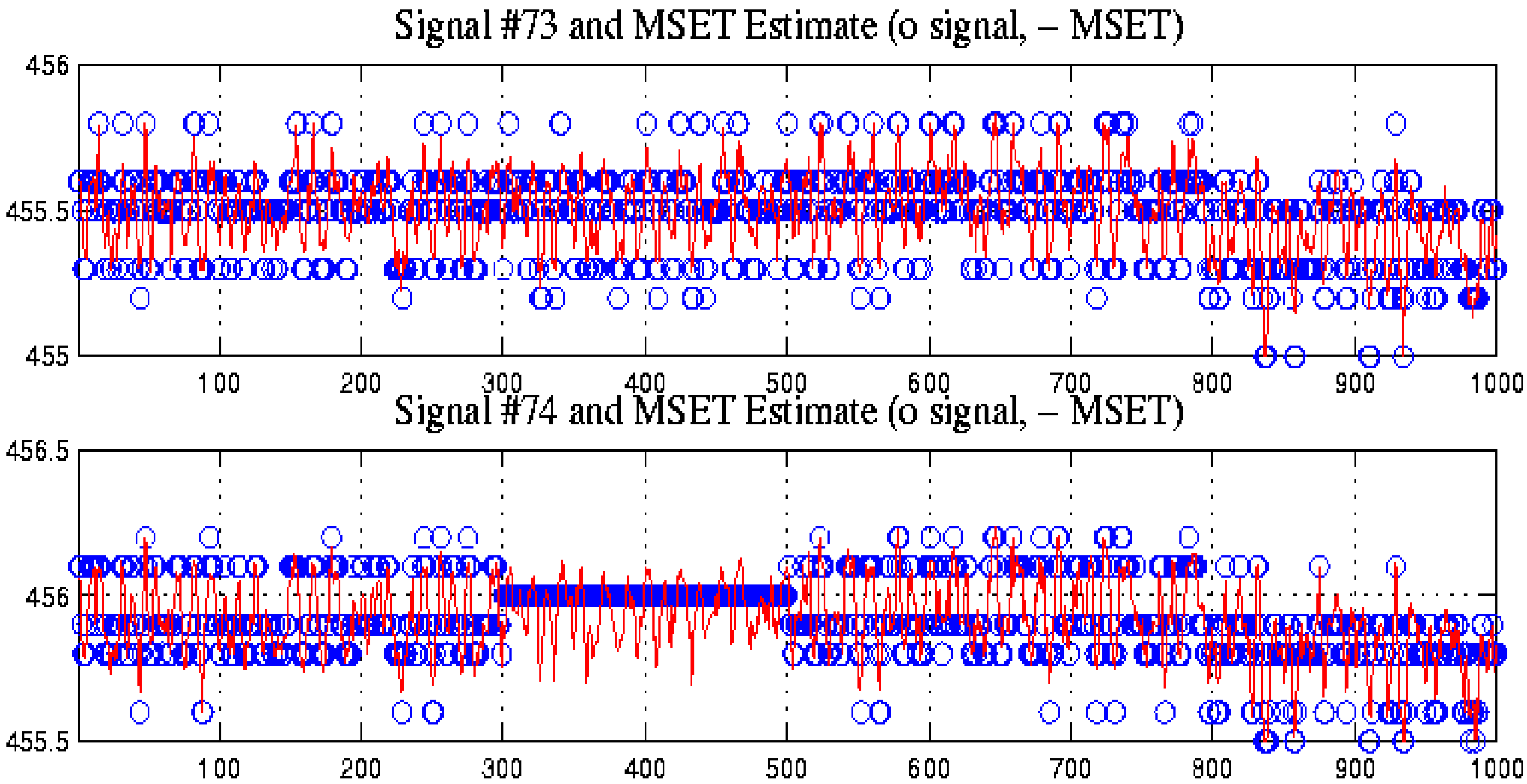


Figure 2.7: Constant signal equal to the average value of the measurements of the signal # 74
O – Original signal, __ MSET estimate.

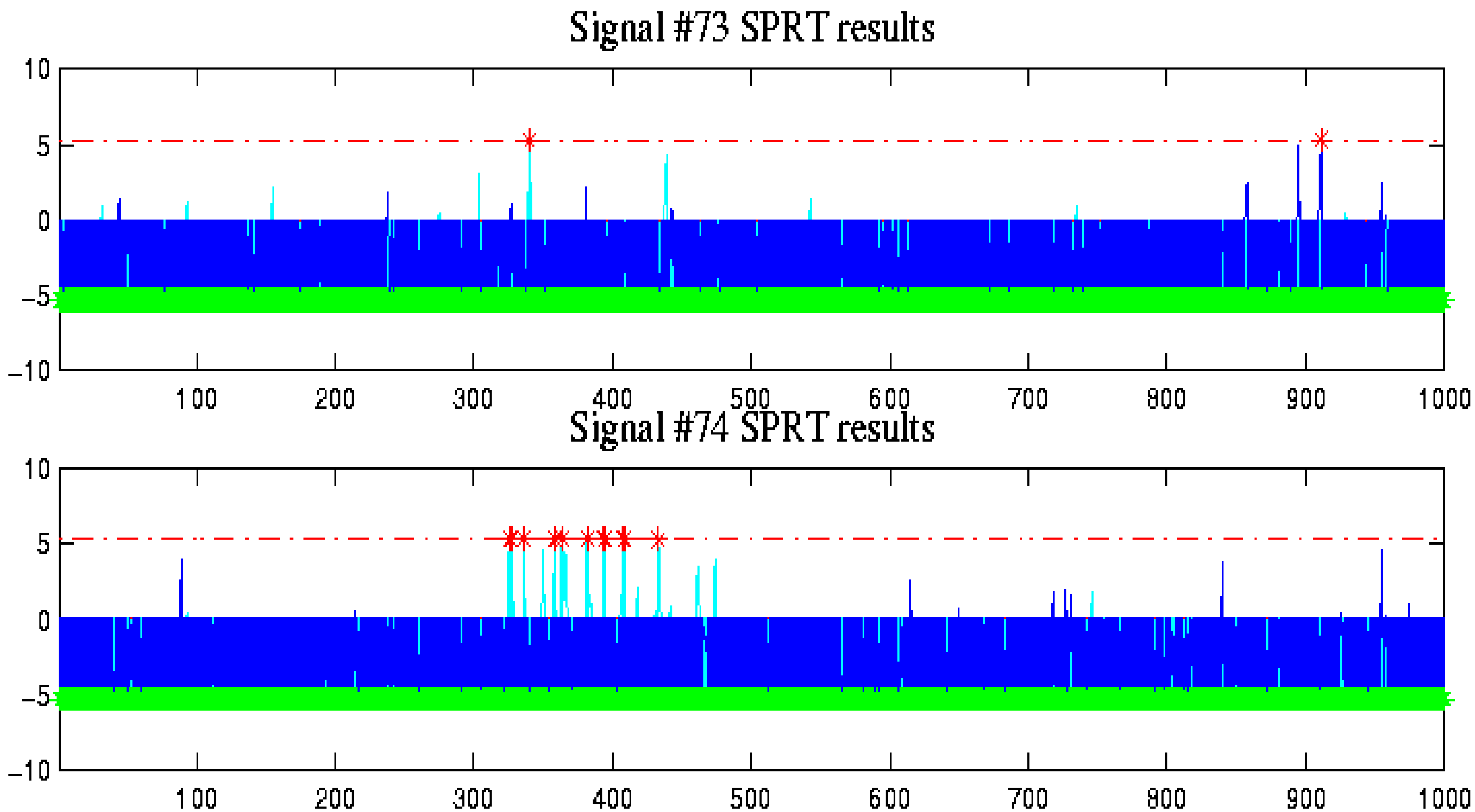


Figure 2.8: Alarm rates (Constant signal equal to the average of the measurements)

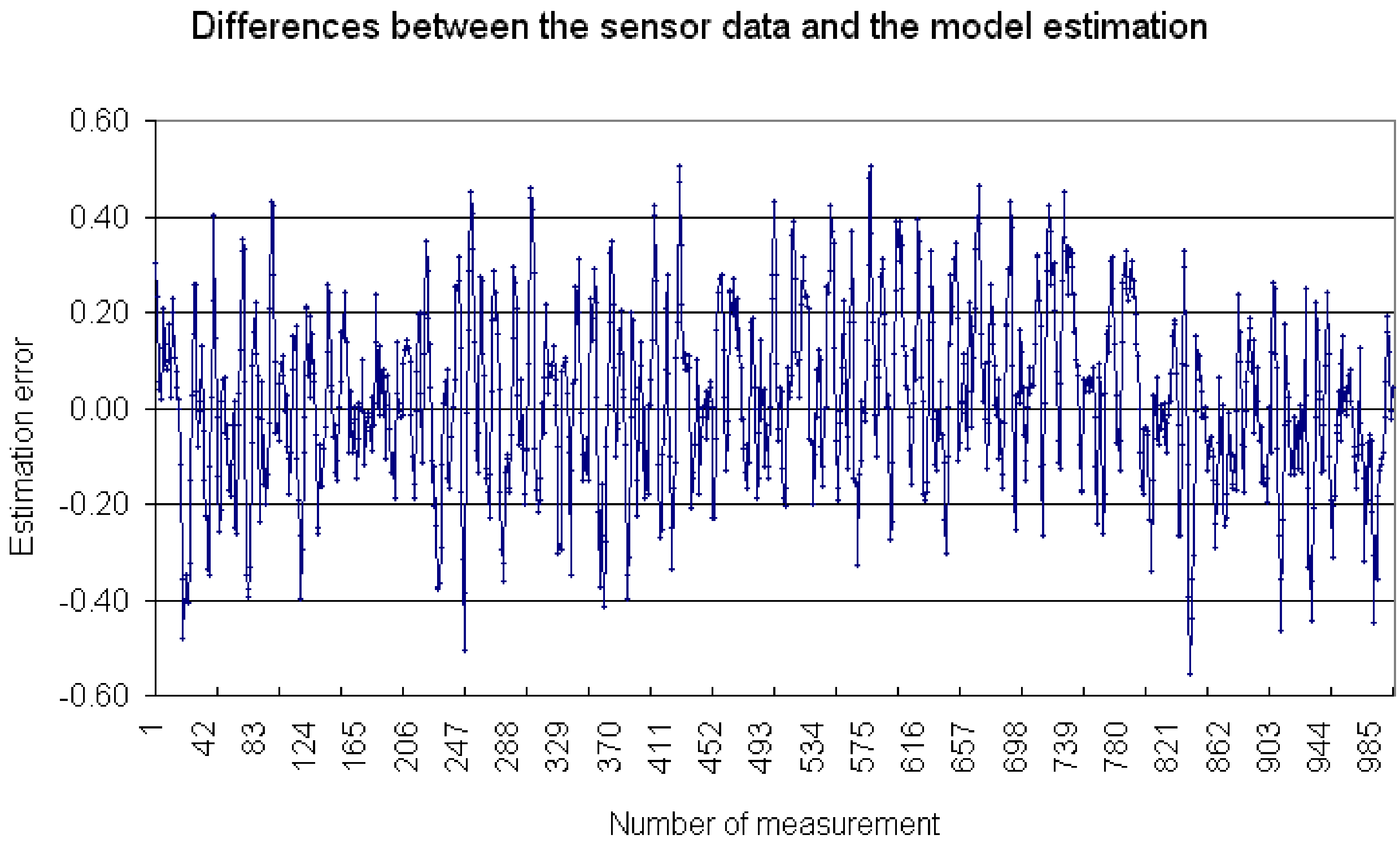


Figure 2.9. Differences between the sensor data and the model estimation for the signal #74 (the average of the absolute relative error was 0.146 which means 0.032% of the average of the measurements)

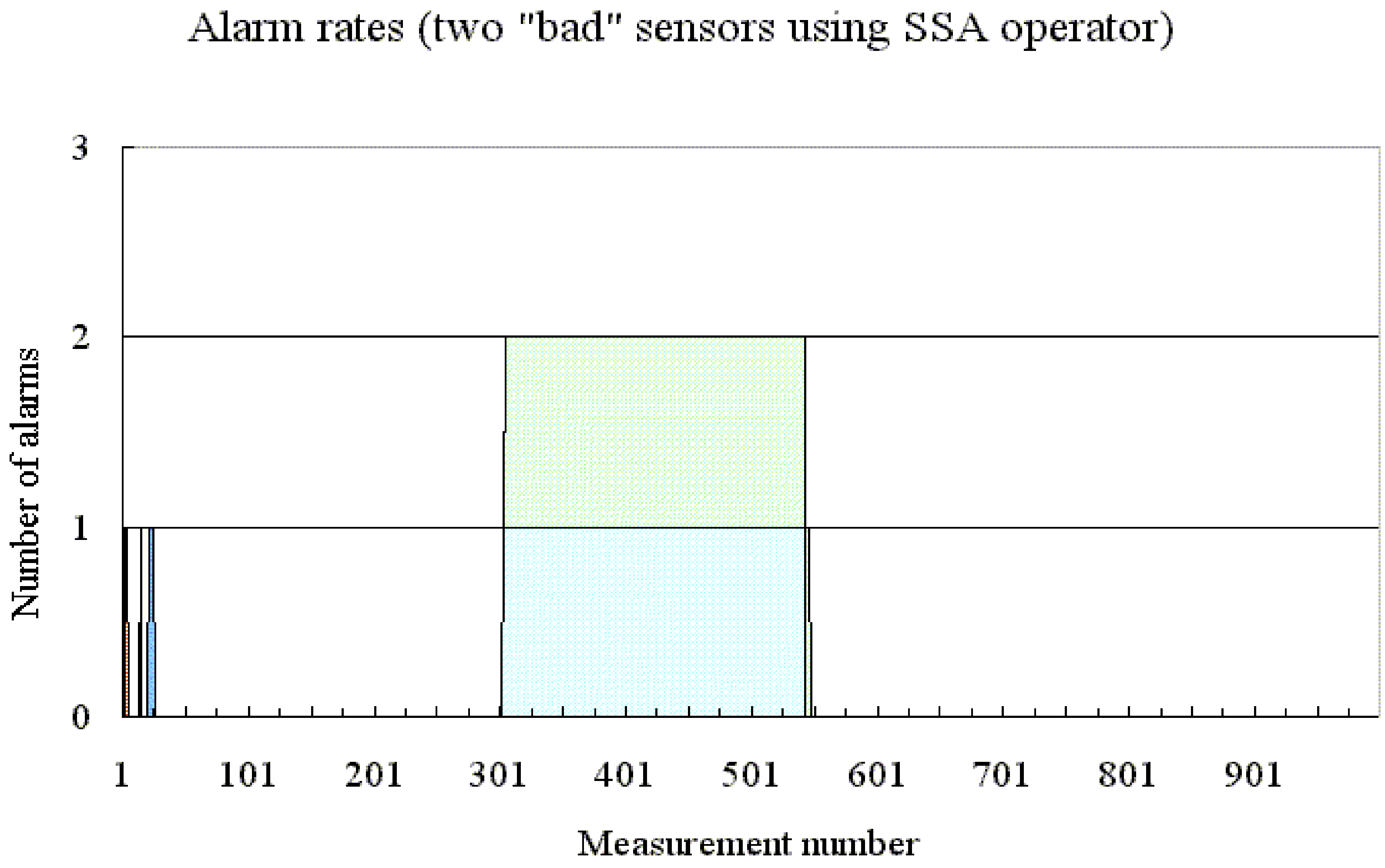


Figure 2.10: Alarm rates using SSA operator (two “bad” sensors in the model, DM= 3, F/MAP= 0.001)

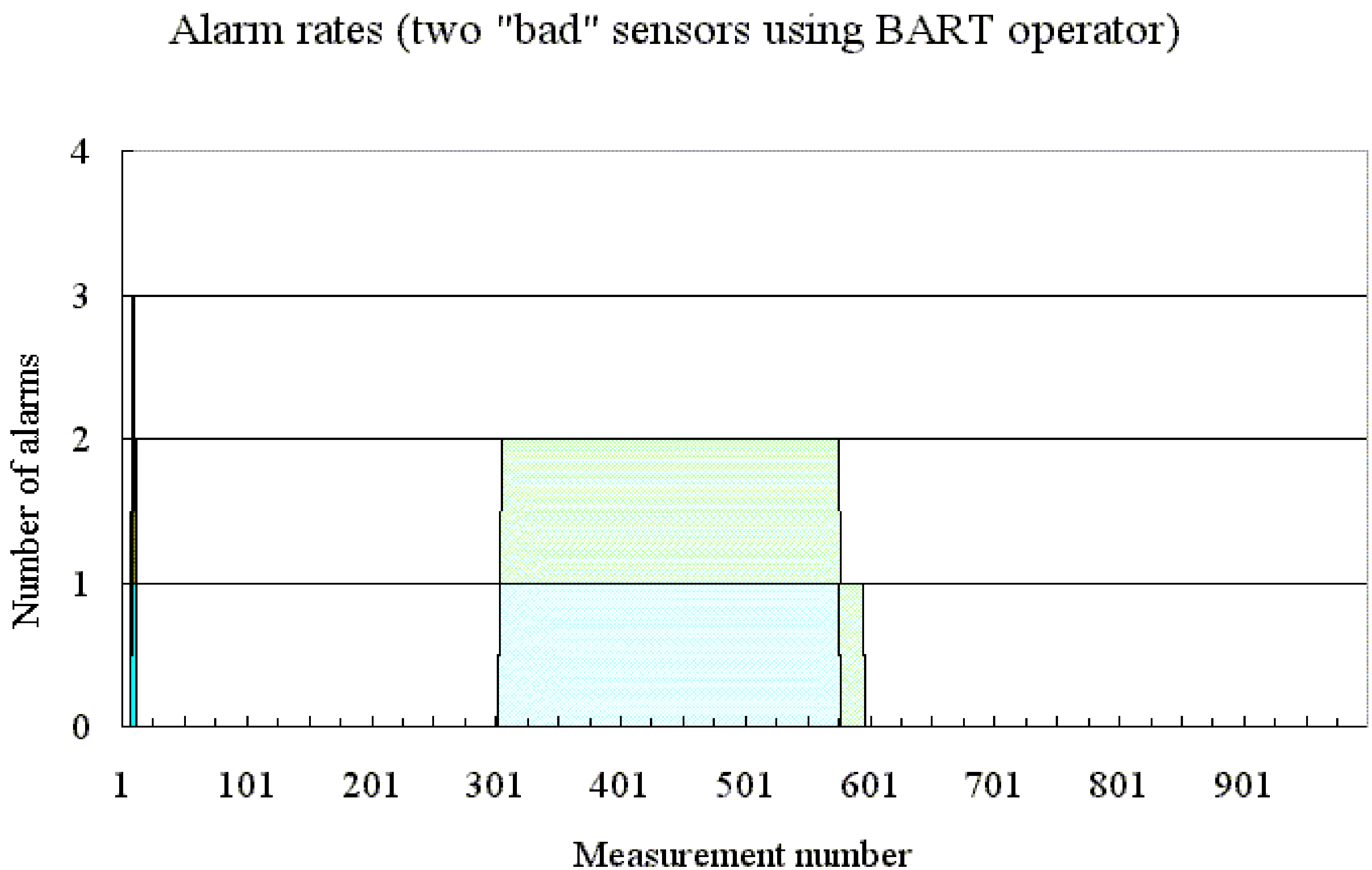


Figure 2.11: Alarm rates using BART operator (two “bad” sensors in the model, DM= 3, F/MAP= 0.001)

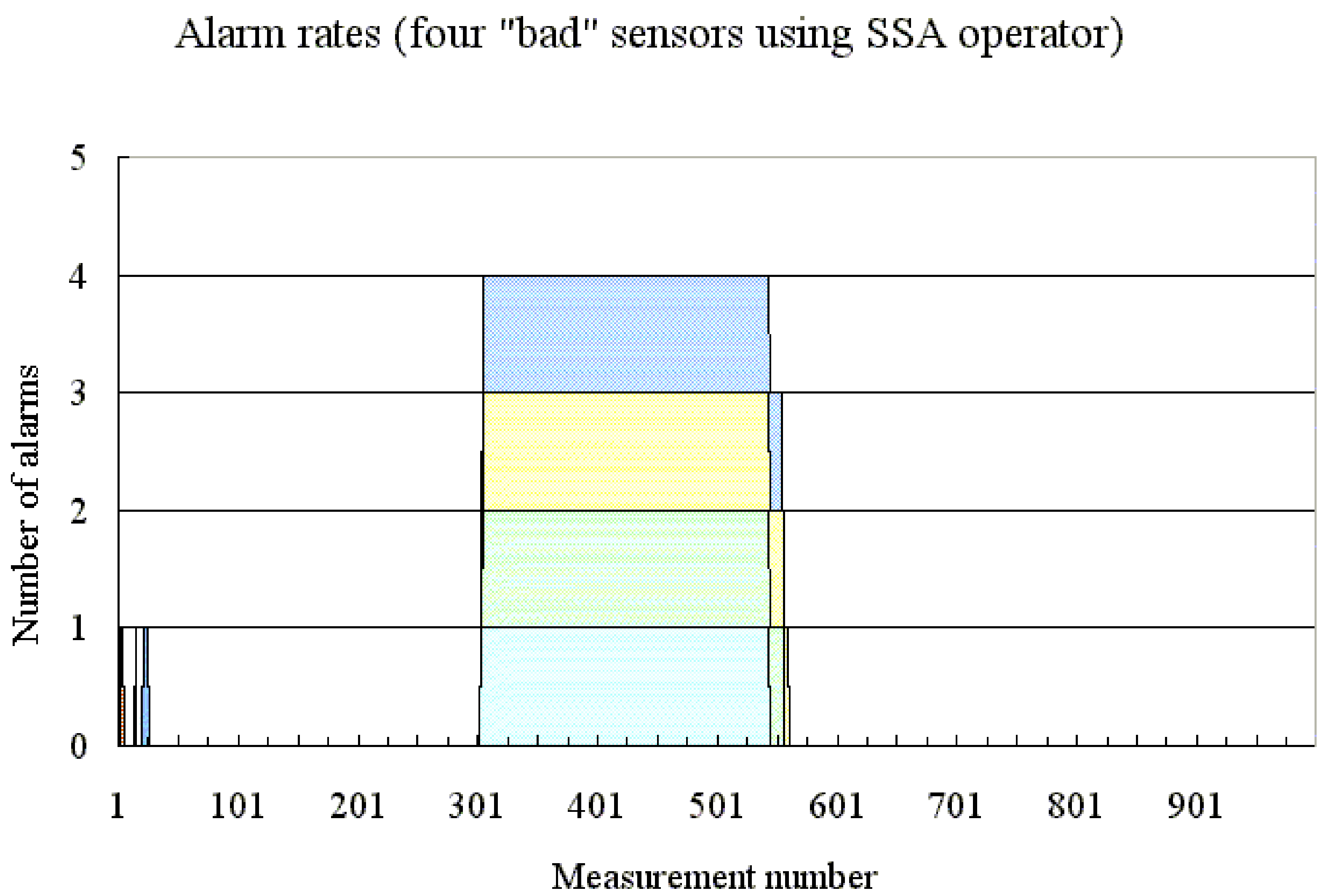


Figure 2.12: Alarm rates using SSA operator (four “bad” sensors in the model, DM= 3, F/MAP= 0.001)

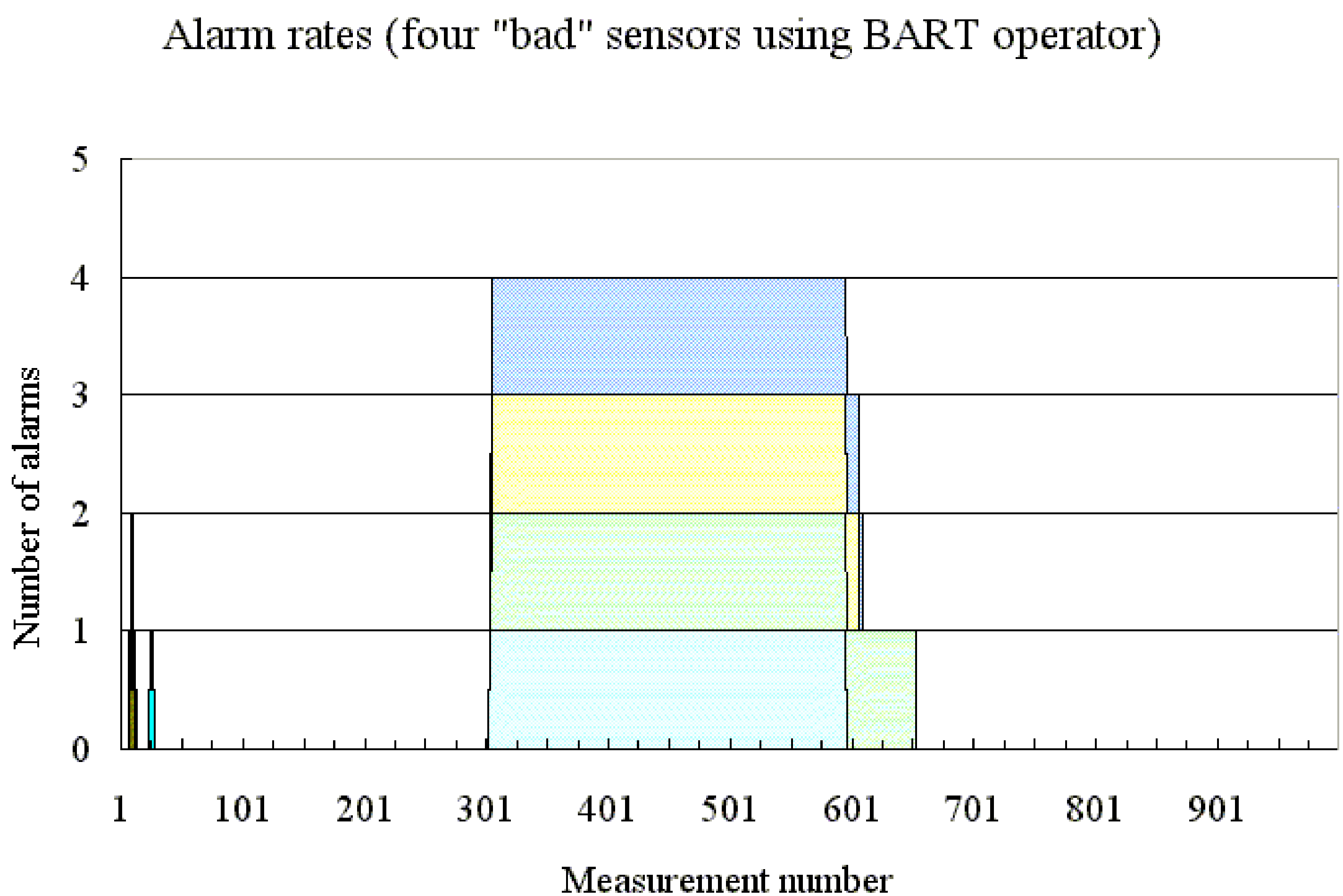


Figure 2.13: Alarm rates using BART operator (four “bad” sensors in the model, DM= 3, F/MAP= 0.001)

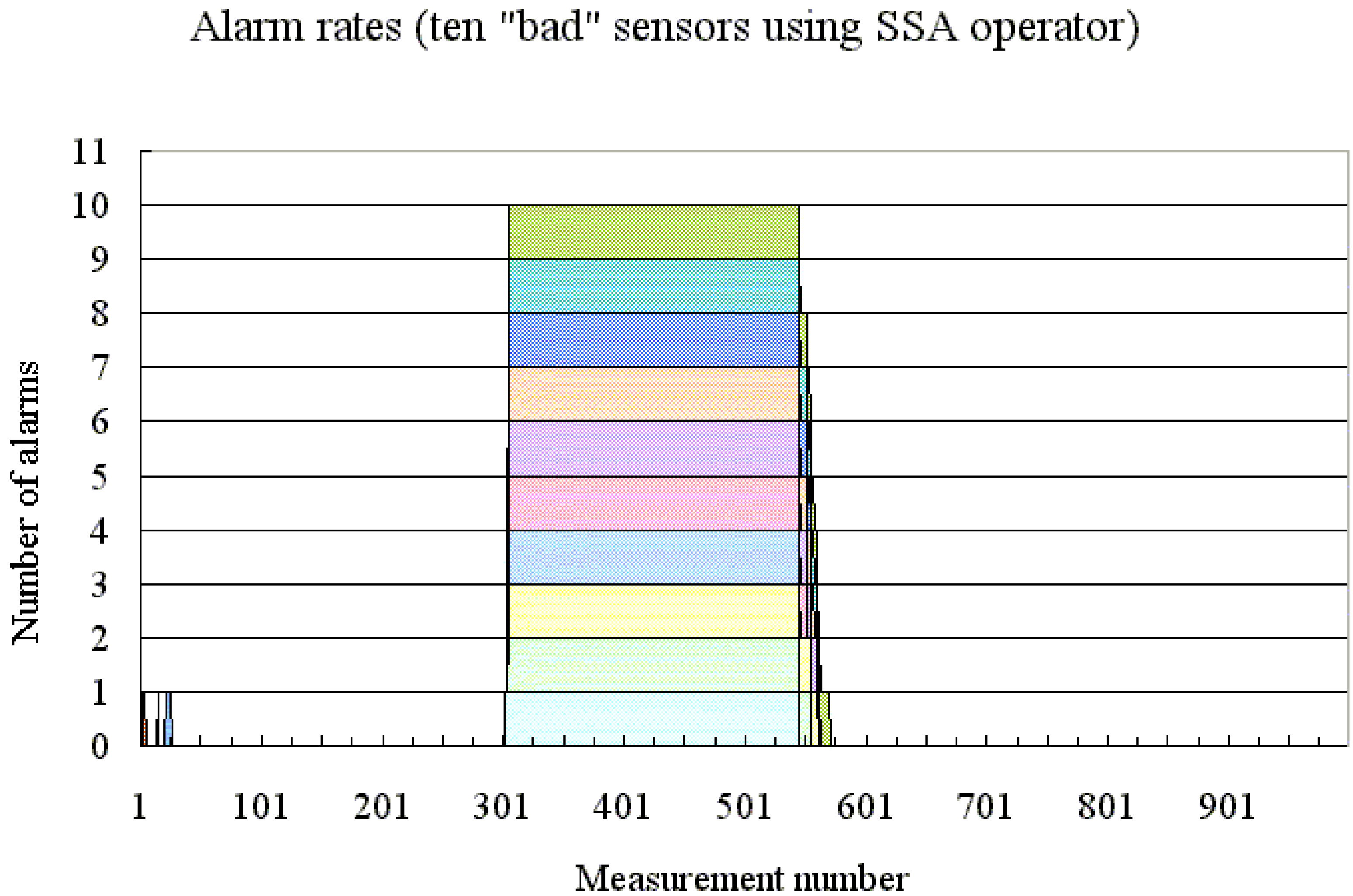


Figure 2.14: Alarm rates using SSA operator (ten “bad” sensors in the model, DM= 3, F/MAP= 0.001

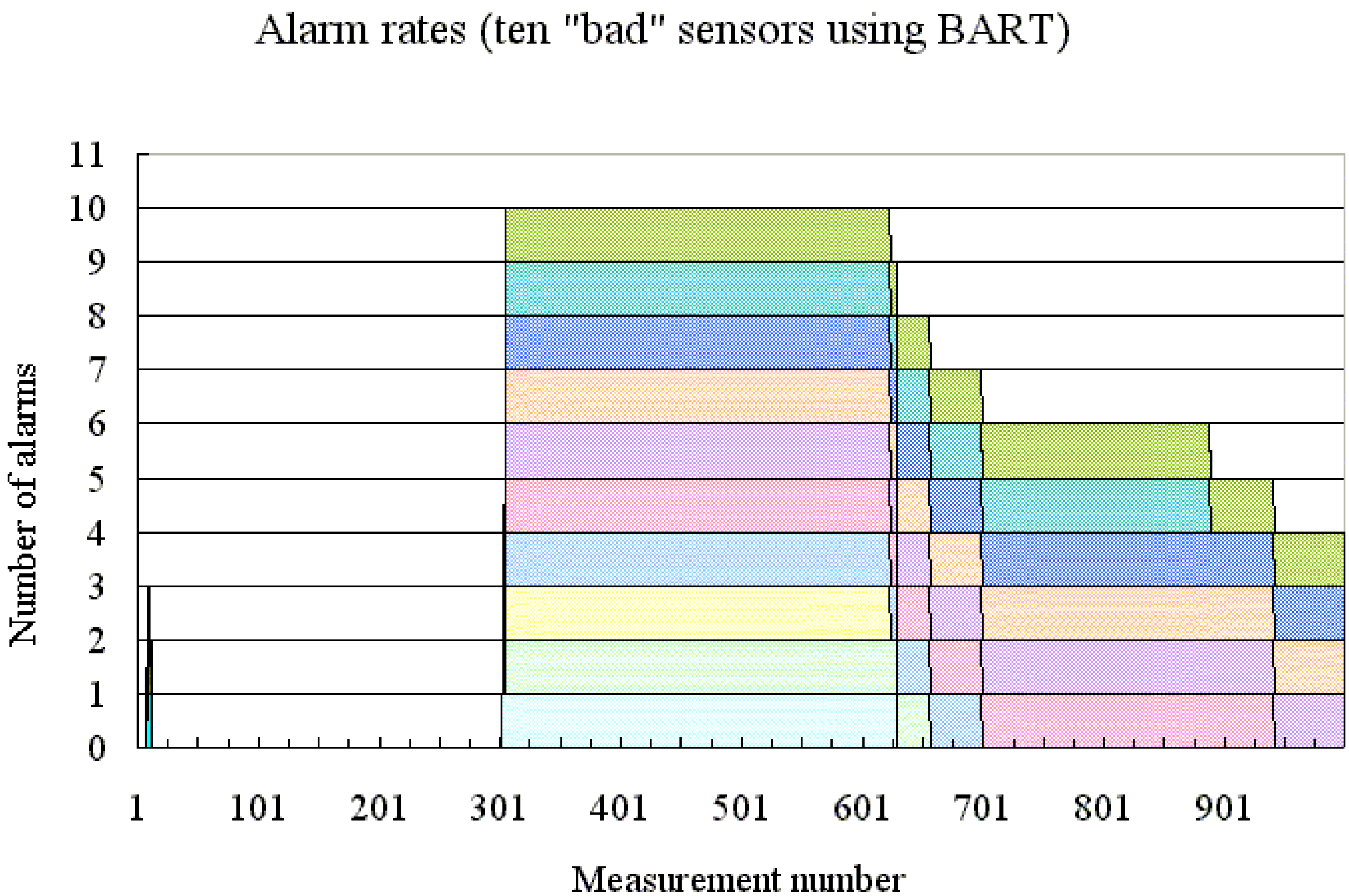


Figure 2.15: Alarm rates using BART operator (ten “bad” sensors in the model, DM= 3, F/MAP= 0.001)

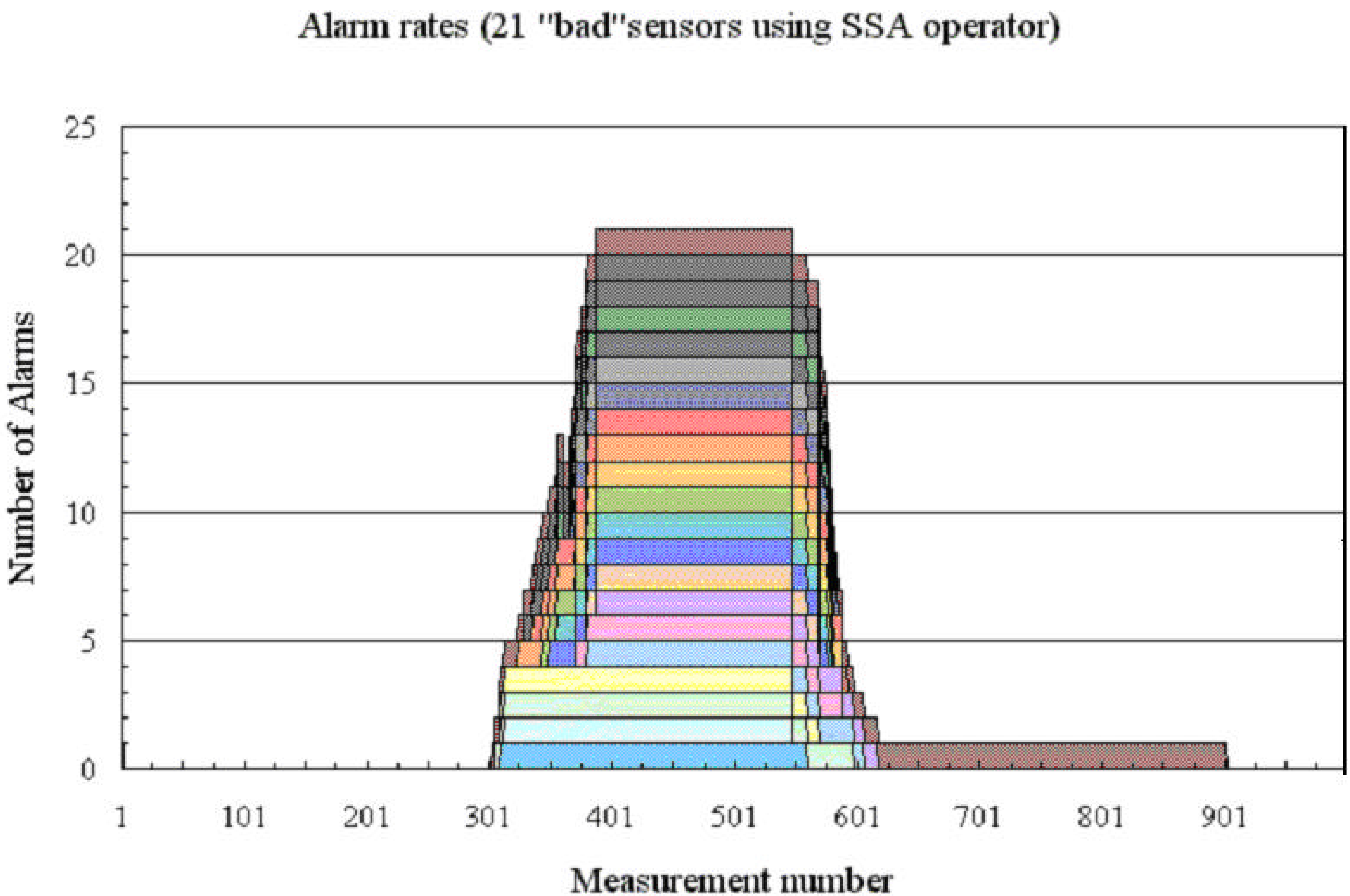


Figure 2.16: Alarm rates using SSA operator (twenty one “bad” sensors in the model, DM= 3, F/MAP= 0.001)

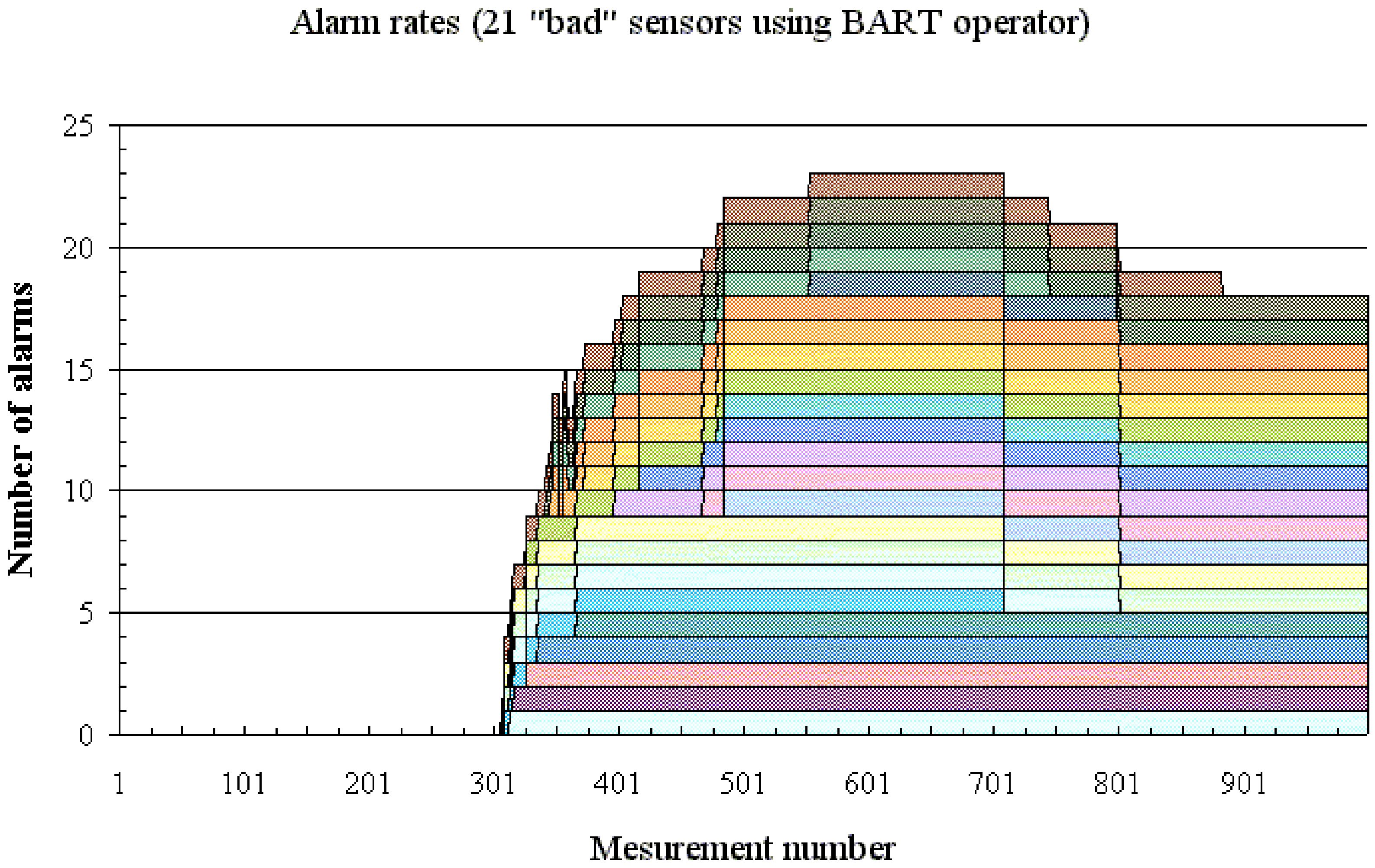


Figure 2.17: Alarm rates using BART operator (twenty one “bad” sensors in the model, DM= 3, F/MAP= 0.001)

3. Phase One Summary & Conclusions

All of the required phase 1 goals were accomplished. DBNPS process computer data was successfully converted into an MSET-compatible format and a sensitivity analysis was performed to select 93 candidate sensors for the MSET model. The 93 selected sensors are listed in **Table 3.1**.

The sensitivity analysis results showed that better system state estimations are obtained when highly correlated sensors are used to construct the system model. When perturbations were introduced, there was no spillover effect, which means that the other sensor estimations were not affected by the degraded sensors. Even for very small perturbations (less than 0.14% of the average) the model was able to detect the “abnormalities” and trigger an alarm. False alarm rates were in concordance with what would expected, less than ten for one thousand measurements (the false alarm probability was set to 0.01).

ANL has developed various non-linear operators to estimate the sensor values such as, the System State Analyzer (SSA), Vector Similarity Evaluation Technique (VSET), Bounded Angular Ratio Test (BART), Arctangent, Vector Pattern Recognizer (VPR), etc [2, 6, 7]. A comparison using the other operators’ results was done. Among all of them BART and SSA had the best results. Using these two operators, the alarm rates were similar for a small number of faulted sensors (less than four).

The study investigated several of the factors that influence the model performance (estimation accuracy and fault tolerance). To study these influences, some factors (sensor selection criteria, the training method and the estimation algorithm) were kept constant. The sensors in the model were selected based on the highest cross correlation coefficients between sensors in the plant and the most important sensors from Heat Balance Computation. Some other statistical tests were done before the sensors were selected. The results showed that better estimations are produced by using sensors in the model that highly correlated.

When all the sensors are operating normally, the investigation demonstrated that the estimations produced using the SSA algorithm were good enough to accomplish the objective of the research. In order to get the best results different values for the false/missed alarm probabilities and for disturbance magnitude need to be tested.

A more detailed description of the Phase 1 results is provided in Reference 8, which is available upon request in electronic format as a PDF file.

Table 3.1: The 93 Sensors included in the MSET-HBS model

No.	Sensor Tag
1	F444
2	F673
3	F674
4	F675
5	F676
6	F679
7	F680
8	F682
9	F859
10	F861
11	F863
12	F864
13	F866
14	F868
15	L879
16	L881
17	L883
18	L884
19	L894
20	P353
21	P354
22	P452
23	P453
24	P454
25	P457
26	P459
27	P474
28	P475
29	P481
30	P482
31	P484
32	P485
33	P490
34	P491
35	P492
36	P589
37	P604
38	P605
39	P606
40	P610
41	P611
42	P612
43	P613
44	P616
45	P617
46	P618
47	P622
48	P623
49	P625
50	P673
51	P674
52	P678
53	P679
54	P686
55	P688
56	P690
57	P696
58	P698
59	P700
60	P721
61	P722
62	P729
63	P730
64	P930
65	P931
66	P932
67	P935
68	P936
69	P937
70	P982
71	T476
72	T477
73	T671
74	T672
75	T678
76	T688
77	T719
78	T720
79	T721
80	T722
81	T728
82	T729
83	T730
84	T731
85	T780
86	T781
87	T800
88	T801
89	T820
90	T821
91	T840
92	T841
93	Z673

4. Phase 2 Objectives

The purpose of the second phase of the project was to:

- Automate the MSET model construction procedure, so that a specific number of highly-correlated sensor signals can easily be determined for any arbitrary set of sensor signals that are considered essential
- Create a workable system for Davis-Besse to determine if a sensor signal in the heat balance calculation is producing an inconsistent value
- Streamline the MSET heat balance model so it is less sensitive to outside of the plant factors such as weather or cooling water temperature
- Study in-depth, the MSET alarm sensitivity with respect to such variables as disturbance magnitude (DM), Missed Alarm Probability (MA), and False Alarm Probability (FA) for the DB heat balance sensor signals
- Create a post-processing program that converts the MSET output into a user-friendly format, and also allows "operationally significant" sensor signal deviations to be a user-specified input, thus permitting the elimination of MSET alarms that are below the operationally significant level.
- The following sections describe briefly how each of these objectives was achieved. *Automation of MSET Model Construction and Data Processing* provides a brief overview of the Excel program that automates the selection of essential sensor signals. *The 28-Sensor DBHB Model* describes the design of a workable MSET model for the Davis-Besse Heat Balance sensors. *The Post-Processing Operational Programs* section gives a brief overview of the Excel programs that convert the MSET output data into a user-friendly a chart and summary. The *Observed Results of Applying the 28-Sensor Model* section provides recommended MSET parameters to create an efficient way for Davis-Besse engineering personnel to evaluate the performance of the sensor signals used in the heat balance calculations.

5. Automation of MSET Model Construction and Data Processing

The following briefly summarizes the Excel program **Sensor signals.xls**. The program automates the determination of the essential sensor signals and creates an output file compatible with the format required for MSET input files.

The automated selection of highly correlated sensor signals for use in the MSET model is performed in a series of different Excel Worksheets. The worksheets are named **Cover Page, Sensor, Correl Sens, Max, Training, Check, Raw Data,** and **Correl**.

The first time the program is being used raw data must be entered into the **Raw Data** worksheet. In the **Raw Data** worksheet, the sensor signal name is entered into cell B1 with the following signals to follow in cells C1, D1 and so forth. To ensure that the data is complete the user can reference the **Check** worksheet to look for any missing values in the data. To compensate for these missing values an average of the previous data points can be calculated by using Excel and "pasted" into the appropriate Excel cell. The missing values must be replaced for the MSET analysis to function properly. After either entering the raw data [or processing the old data] the user then goes to the **Cover Page**.

On the **Cover Page**, the total number of sensor signals desired and also the sensor signals that are considered "essential" for the calculation are entered. The essential sensor signals help determine which other signals are selected by determining signals that are highly correlated with the "essential" sensor signals for the model that being constructed. After the "essential sensor signals" are entered, the user clicks the first E*nter* [or *run macro*] button and after a few seconds of calculations the program produces a revised **Cover Page** to the user's monitoring device. The program then requires additional information for two different worksheets. The first worksheet is the **Correl Sens** worksheet. After this information has been entered, the second *Enter* button on the **Cover Page** is clicked to start another macro. After a few seconds of calculations, the program produces a revised **Cover Page** with the highest-correlated sensor signals listed by rank along with their correlation value percentage. The final step, save the selected sensor signals for MSET input data.

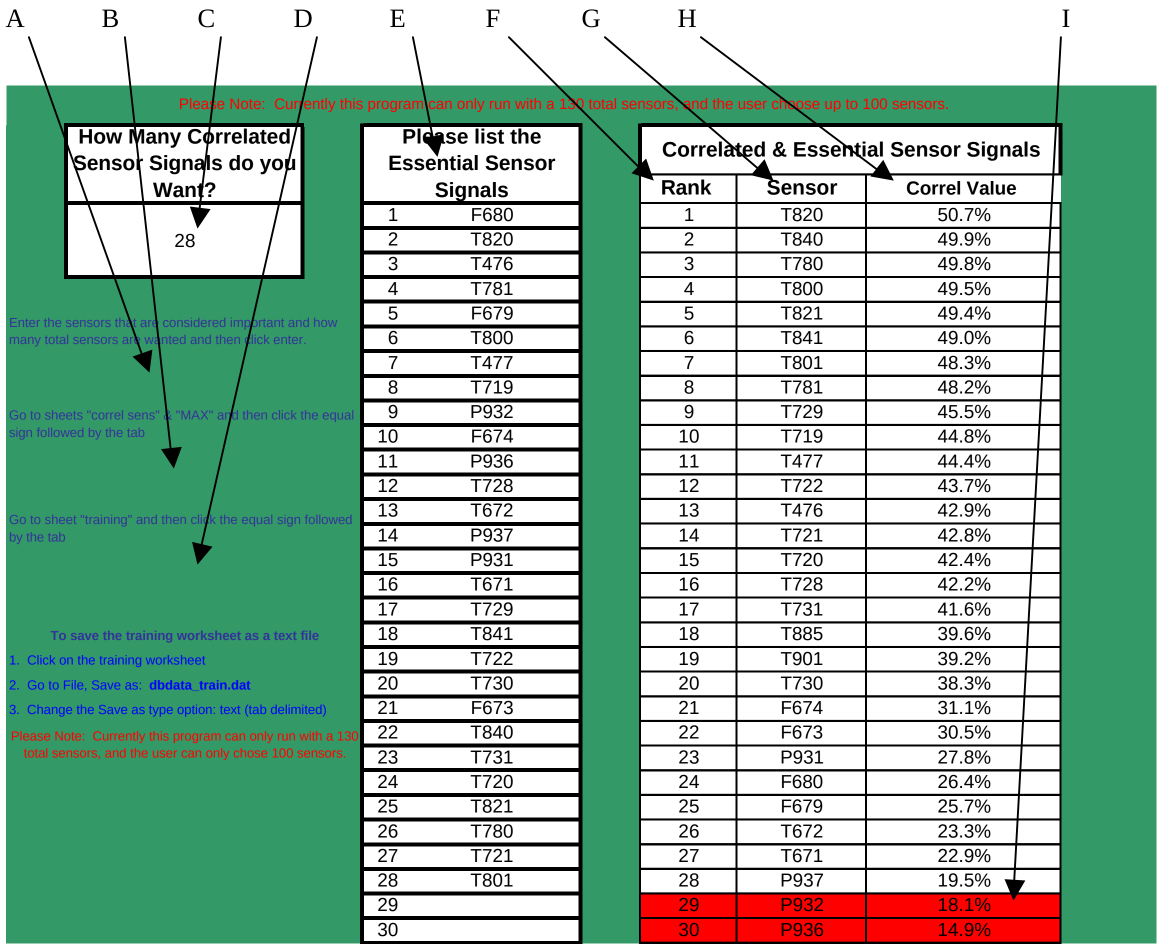
The following graphics **Raw Data, Cover Page, Correl Sens, Max,** and **training** provide a visual description of contents of each page. Further details about the pages are available in Reference 9.

Figure 5.1 Excel Raw Data Worksheet Illustration

Data is entered into column B

B	C	D	E	F	G	H	I	J	K	L	
F673	F674	F679	F680	T476	T477	T671	T672	T719	T720	T721	T722
5859	5830	5782	5799	589.7	590.9	455	455.6	605.7	607.2	606	607.2
5851	5808	5743	5745	589.9	591.2	454.9	455.5	605.8	607.5	606.2	607.5
5863	5839	5804	5827	589.9	591	455	455.6	605.9	607.4	606.1	607.4
5893	5868	5799	5818	589.9	591	454.9	455.5	605.8	607.3	606.2	607.4
5856	5822	5767	5803	589.9	591	455	455.6	605.8	607.3	606.1	607.2
5869	5825	5796	5808	589.9	591	455	455.5	605.8	607.1	606.2	607.3
5847	5816	5779	5799	589.9	591	455	455.6	605.8	607.3	606.1	607.3
5869	5840	5779	5808	589.9	591	455	455.5	605.8	607.2	606.1	607.3
5874	5833	5791	5798	589.9	591	455	455.6	605.8	607.2	606.1	607.2
5878	5847	5762	5796	589.9	591	455	455.6	605.8	607.5	606	607.5
5874	5835	5784	5816	589.7	591	455	455.6	605.8	607.4	606.1	607.2
5823	5799	5757	5784	589.9	591	455	455.6	605.8	607.4	606.2	607.4
5780	5746	5736	5774	589.9	591.2	454.9	455.5	605.9	607.5	606.4	607.5
5871	5849	5787	5820	590	591.3	454.9	455.5	605.9	607.1	606	607.3
5869	5822	5758	5782	590	591.3	454.6	455.2	605.8	607.2	606	607.2
5909	5871	5787	5827	589.9	591	454.6	455.2	605.7	607.4	606.1	607.4
5871	5837	5787	5820	589.9	591.2	454.9	455.5	605.9	607.5	606.2	607.5
5849	5820	5789	5794	589.9	591	455	455.6	605.9	607.5	606.1	607.5
5863	5832	5789	5811	590	591.2	455.2	455.8	605.9	607.5	606.3	607.5
5864	5835	5779	5804	590	591.2	455.2	455.8	606	607.5	606.1	607.5
5844	5806	5767	5798	590	591.2	455	455.6	605.9	607.6	606.2	607.5
5873	5844	5772	5796	590	591.2	455	455.6	606	607.6	606.3	607.5
5871	5842	5763	5794	590.2	591.3	455	455.6	606	607.4	606.3	607.4
5842	5811	5746	5786	590.2	591.3	455	455.6	606	607.6	606.4	607.7
5840	5815	5726	5762	590.3	591.5	454.9	455.5	606	607.6	606.4	607.7

Figure 5.2 Excel Cover Page Worksheet Illustration



Please list the Essential Sensor Signals	
1	F680
2	T820
3	T476
4	T781
5	F679
6	T800
7	T477
8	T719
9	P932
10	F674
11	P936
12	T728
13	T672
14	P937
15	P931
16	T671
17	T729
18	T841
19	T722
20	T730
21	F673
22	T840
23	T731
24	T720
25	T821
26	T780
27	T721
28	T801
29	
30	

Correlated & Essential Sensor Signals		
Rank	Sensor	Correl Value
1	T820	50.7%
2	T840	49.9%
3	T780	49.8%
4	T800	49.5%
5	T821	49.4%
6	T841	49.0%
7	T801	48.3%
8	T781	48.2%
9	T729	45.5%
10	T719	44.8%
11	T477	44.4%
12	T722	43.7%
13	T476	42.9%
14	T721	42.8%
15	T720	42.4%
16	T728	42.2%
17	T731	41.6%
18	T885	39.6%
19	T901	39.2%
20	T730	38.3%
21	F674	31.1%
22	F673	30.5%
23	P931	27.8%
24	F680	26.4%
25	F679	25.7%
26	T672	23.3%
27	T671	22.9%
28	P937	19.5%
29	P932	18.1%
30	P936	14.9%

A: Is where the first macro button is listed, even though it is not shown on this demonstration page, this is the location of the first macro button.

B: The second macro button (Not Shown)

C: The location where the total number of sensor signals is entered.

D: The third and final macro button (Also Not Shown)

E: The list where the essential sensor signals are entered. Entered in a list fashion.

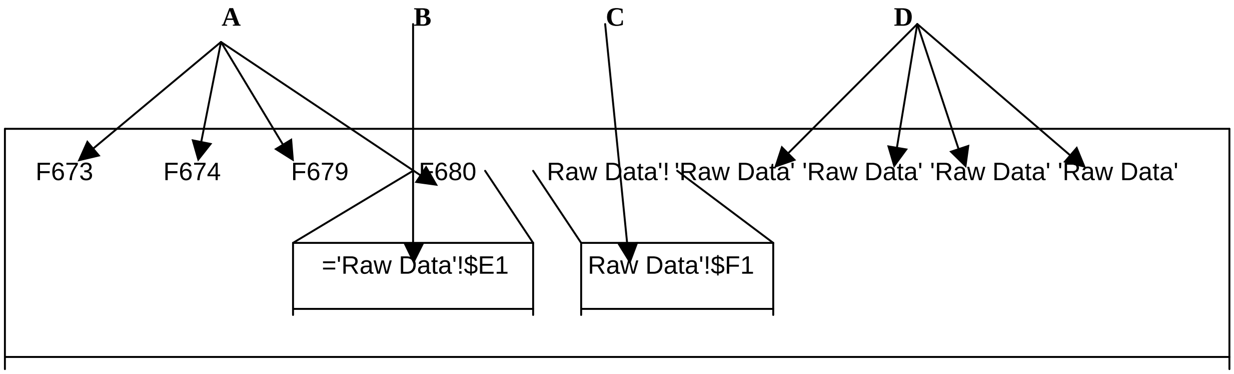
F: The Rank of the most-correlated sensor signals

G: The actual name of the most-correlated sensor from highest correlated to least.

H: The Correl Value listed as percent

I: Those sensor signals that were entered as essential, but did not make the top correlated sensor signals that were inputted in location C. These cells were show up red.

Figure 5.3 Excel Correl Sens & Training Worksheet Illustrations



The illustration shows how the **Correl Sens** and **Training** worksheet should look like while adding the “=” sign.

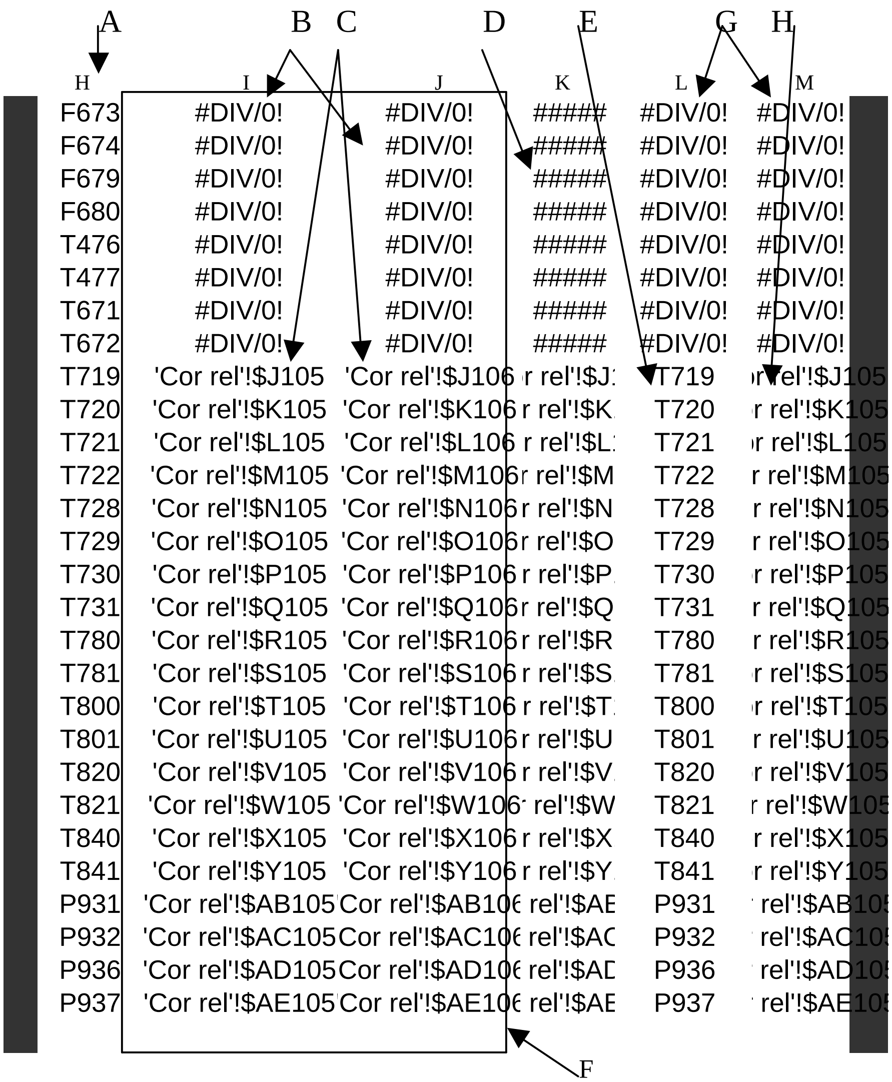
A: Shows the contents of the cell after the “=” has been added.

B: Shows the formula of the cell after the “=” has been added.

C: Shows the formula of the cell before the “=” has been added.

D: Shows the contents of the cell before the “=” has been added.

Figure 5.4 Excel Max Worksheet Illustration



This worksheet demonstrates how the "=" is inserted into the formula.

A: Sensor's Name

B: Columns I and J after the "=" has been inserted into the formula

C: Columns I and J before the "=" had been inserted into the formula

D: What Column K should look like after the "=" has been inserted in Columns I & J

E: What Column L looks like before the "=" has been inserted in Columns I & J

F: The highlighted box around Columns I & J to make the "=" insertion easier.

G: What Columns L and M look like after the "=" has been inserted in Columns I & J

H: What Column M looks like before the "=" has been inserted in Columns I & J

6. The 28-Sensor DBHB Model

As a result of preliminary Phase 2 studies it was determined that sensors T885 and T901 needed to be eliminated from the Davis-Besse MSET heat balance sensor model. The signals from these two sensors are highly "quantized" and undergo significant distribution shifts week to week. For the MSET methodology to work properly, the input distributions must be relatively constant have at least approximately normal (or Gaussian) distributions. Without these types of input distributions, fundamental assumptions of the methodology are not met and MSET results are flawed. Another reason supporting the elimination of T885 and T901 is that their outputs are not used in the heat balance calculation, and hence their elimination from the MSET model has no effect on the heat balance calculations. The result of eliminating these two sensors was to create a 28-Sensor model.

Several sets of numerical experiments were performed to answer these questions. The 28-sensor MSET model was tested on a series of weekly data sets constant training data. The training data for the single data set was May 22, while the training data for the double data sets were combinations of (May 22 – May 30), (June 5 – June 12), (May 22 – June 5), and (May 30 – June 12) data sets. The results of these experiments gave the insight needed to determine, whether single or double data set technique produced better results.

6.1 Single Data Set Experiments

The single data experiments used the May 22 data set as the training data and all of the other data sets as the testing data. The MSET results of these tests are listed in Table 6.1. At first, the May 22 training data set was very successful with no alarms appearing for either May 30 or June 5. However as the test data sets became further and further away (time-wise) from May 22, more and more alarms started to appear.

With June 12 test data set, two alarms were recorded for a DM value of 5, T671 with 128 alarms and T672 with 112 alarms. When the DM value was increased to 7 to 10 and then to 12 the number of alarms was reduced for both sensors. The T671 alarms dropped from 113 to 88 and then finally to 59 for a DM value of 12. The T672 alarms dropped from 81 to 68 to finally no alarms for a DM value of 12. The T671 alarms did not drop out even when the DM parameter was increased to 25, where 47 alarms were still recorded.

For June 19 as the testing data, there were three alarms at a DM value of 5, T477 with 1173, T719 with 99, and T721 with 11. When DM parameter was increased, the alarms eventually dropped out with T719 having no alarms at a DM value of 7, T721 having no alarms at a DM value of 15, and T477 having no alarms at a DM value of 20.

With June 26 as the test data set, two alarms existed at a DM value of 5, T477 with 381 alarms and P932 with 1306 alarms. At a DM value of 7, T477 had 31 alarms, while P932 had none. At a DM value of 10, no alarms were present for T477. The June 26 test data set is a reassuring sign that the MSET model can go more than a month. Another reassuring sign was that July 3 had no alarms for a DM value of 5.

However for test data sets, after July 3, MSET alarms started to increase drastically. The July 10 data set produced an extensive number of alarms at DM value of 5, T477 with 1314 alarms and T671 with 687 alarms. These alarms did decrease as the DM value increased with the T477 alarms finally dropping out at a DM value of 15. However, the T671 alarms were never eliminated and 14 alarms T671 were recorded even for a DM value of 25.

The July 17 data set produced one large set of alarms at a DM value of 5, T477 with 1309 alarms. The T477 alarm numbers did not decrease rapidly even when the DM parameter increased and never drop out completely. Sensor signal T477 had 853 alarms at a DM value of 25.

July 24 started with three alarms at a DM value of 5, T477 with 1318 alarms, T671 with 160 alarms, and T721 with 7 alarms. The T721 alarm was not significant as it dropped out right away with a DM value of 10. The T671 alarm finally dropped out at a DM value of 20; however T477 is very disturbing not because it never dropped out, but because its alarms never decreased but stayed the same at 1318 alarms all the way to a DM value of 25. Either the May 22 is no longer a good training data set and the MSET model needs to be retrained or the sensor signal T477 is failing. The average for T477 for July 24 is the lowest average with a temperature of 591.10 F, which is 0.10 degrees lower than July 17; however July 17 also had alarms for T477 that never dropped out. The July 24 average is 0.30 degrees lower than the training data of May 22, which is the second largest average. The July 24 distribution is also the lowest distribution with most of its counts being –0.6, -0.4, and –0.2. There are two explanations for the large amount of T477 alarms in the July 24 data, the first is that the sensor T477 is starting to fail, while the second is that the training data set needs to be retrained. The T477 signal histogram [Reference 9, page A.7] shows that the sensor T477 values are starting to drift.

If the T477 signal value is considered to be drifting or failing, then the single data set technique is working very consistently. Alarms appear, but can usually be eliminated by increasing the value of DM parameter. While it is not recommend, having a large DM's a post-processing program, which allows users to, input sensor's sensitivities can eliminate most of these alarms. If the T477 signal value is not failing, then the single data technique is not working after 2-½ months and MSET must be retrained in order to continue to use the single data set technique.

Table 6.1 Single Data MSET Results

Figure 7.2 Excel Cover Worksheet Illustration

A	D	E	H	I	M	N	R	S	W	X	AB	A
Sensor	**Ave - Xi**	**# Alarms**	**Ave - Xi**	**# Alarms**	**Ave - Xi**	**# Alarms**	**Ave - Xi**	**# Alarms**	**Ave - Xi**	**# Alarms**	**Ave - Xi**	**# Ala**
F673	70.328	1	61.328	1	60.328	5	58.328	1	56.328	2	54.328	3
F674	67.584	2	62.584	1	60.584	2	55.584	2	53.584	2	52.584	3
F679	60.078	2	54.078	1	51.078	1	48.078	1	44.078	2	42.078	4
F680	65.652	1	51.652	1	48.652	1	46.652	2	44.652	1	43.652	3
T476	0.212	6	0.112	12			0.088	15	0.188	4	11.588	4
T477	0.222	4	0.122	14			0.078	9	0.178	6	11.578	2
T671	0.204	2	0.104	12	0.004	13			0.196	10	8.696	1
T672	0.376	3	0.176	13	0.076	5			0.124	6	0.224	3
T719	0.281	5	0.181	25	0.081	74			0.019	112	0.119	5
T720	0.398	1	0.198	5	0.098	9			0.002	8	0.102	6
T721	0.140	5	0.040	9			0.060	8	0.160	10	11.960	4
T722	0.419	1	0.319	1	0.219	4	0.119	9	0.019	12		
T728	0.313	1	0.213	3	0.113	9	0.013	11			0.087	7
T729	0.166	4	0.066	8			0.034	12	0.134	18	0.234	6
T730	0.285	3	0.185	3	0.085	4			0.015	11	0.115	1
T731	0.238	8	0.138	4	0.038	9			0.062	8	0.162	1
T780	0.307	5	0.207	6	0.107	10	0.007	13			0.093	4
T781	0.423	3	0.223	5	0.123	8			0.077	6	0.177	5
T800	0.440	2	0.340	4	0.240	6	0.140	12	0.040	11		
T801	0.639	1	0.539	1	0.339	1	0.239	10	0.039	6		
T820	0.266	2	0.166	9	0.066	7			0.034	10	0.134	5
T821	0.295	2	0.195	7			0.005	9	0.105	16	0.305	6
T840	0.522	1	0.422	2	0.322	5	0.222	14	0.122	11	0.022	6
T841	0.382	2	0.282	9	0.082	14			0.018	8	0.218	4
P931	7.066	1	5.866	1	5.366	1	4.766	1	4.566	3	4.466	1
P932	9.543	1	8.043	1	7.543	1	7.343	2	7.043	1	6.943	1
P936	13.501	1	11.401	1	11.001	1	8.801	1	8.401	1	8.101	2
P937	7.894	1	7.594	1	6.694	1	6.494	1	6.294	1	6.194	1

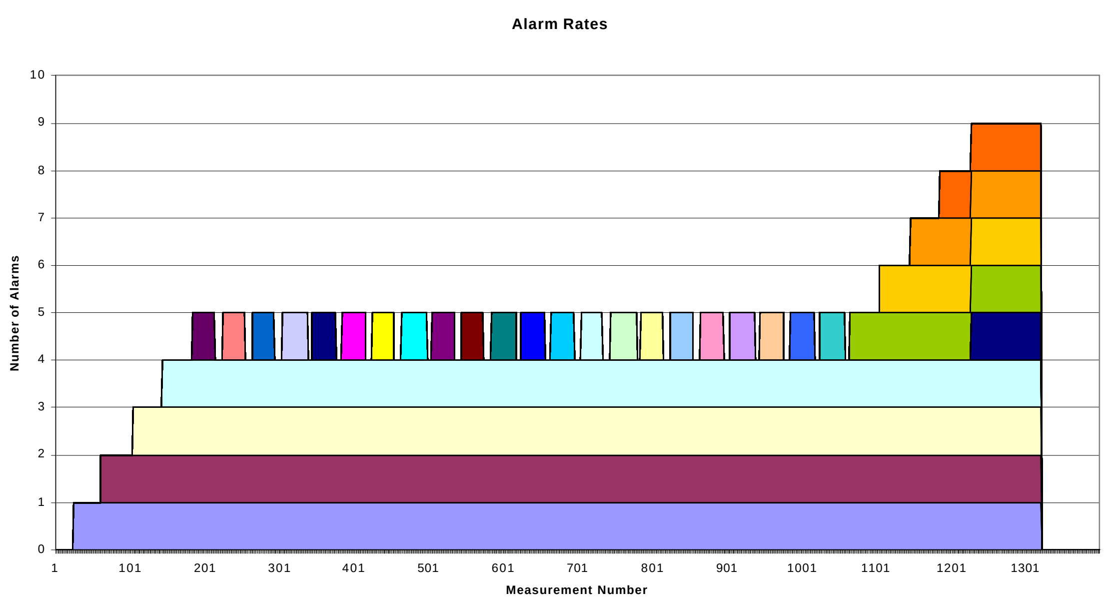
The letters at the top of this figure represent the Excel column letters. Each letter corresponds to the previous description. Columns D, (Ave-Xi) represent the actual deviation of the alarm sensor signals. The columns E, I, N, S, X, AC, and AH (# Alarms) represent the nu each deviation. Column A is linked to the **Sensitivity** worksheet. If a column is blank, this is where no deviation occurs; hence the bla

Data: This worksheet compares the calculated deviation with the user’s sensitivity deviation. This worksheet uses an IF statement to compare the two values. The syntax “*=IF(Sensitivity!$G$2=0,””,IF(ABS(Results!A1) <= Sensitivity!$G$2,0,1))*” does the comparison. The first IF statements ask if a cell on the **Sensitivity** worksheet is equal to “0”, if this is true then nothing is placed in the cell. This IF statement will ensure that only cells that represent sensor signals will have a value placed in them. The second IF statement compares the calculated deviation with the sensitivity deviation. The syntax “*IF(ABS(Results!A1) <= Sensitivity!$G$2,0,1*” compares the two deviations. If the absolute value of the calculated deviation is greater than the sensitivity deviation, then a “1” is placed in that particular cell. If the sensitivity deviation is greater than the calculated deviation then a “0” is placed in that particular cell.

Sensitivity: This worksheet is where the user enters both the desired alarm cut-off levels and the sensor signal names. The user enters the cut-off levels either as a percentage or as the actual deviation. The first column is the sensor’s name, which must be in the same order as the input files dbdata_train and dbdata_test. Column B informs Excel on whether the user entered the cut-off as a percentage or as the actual deviation. If a 1 is entered, the cut-off is a percentage deviation, while a 2 represents the cut-off as the actual deviation. The next two columns, C and D, are where the user enters the cut-off values. Column C is a percentage deviation, while column D is the actual deviation. Column E is the average of the train data. Column E is used in the calculation for both the sensitivity deviation and the subtraction from the individual data for that sensor. The syntax is “*=IF(train!A2,AVERAGE(train!$A:A),0)*”. The IF statement determines if there is any sort of data in the corresponding **train** sheet, if there is no data then a “0” is place in the cell. If there is data in the corresponding cell, then the AVERAGE function finds the average for the corresponding **train** worksheet column. Column F is the percentage of the sensitivity deviation. The syntax is “*=IF(B2=1,D2/E2,C2)*”. The IF statement determines whether the user inputted the cut-off level as a percentage deviation or the actual deviation. If the user entered the percentage (1), the IF statement uses the value from column C. If the user entered the standard deviation (2), the column takes the inputted deviation from column D divided by the average of column E. Column G calculates the sensitivity deviation from the average in column E and the percentage in column F. The syntax is “*=IF(E2=0,,ABS(E2-(E2*(F2+1))))*”. The IF statement places a “0” in those columns with no sensor signals. The ABS is for the absolute value of the average subtract the average multiplied by the percentage plus 1, [average – average*(percentage + 1.0)]. This calculation produces the value of the cut-off deviation used by the program to compare against the actual deviation. This comparison is performed in the **Data** worksheet.

Alarm Rates: This worksheet is a simply area chart of the **Data** worksheet. A nice feature of this worksheet is that it determines which sensor signals are giving alarms. All the user has to do is place the mouse over the alarm and the sensor name will appear. This feature is made possible by the “Source Data” function that appears on the right mouse click followed by clicking on the “Series” page and going to the box called “Name” where the following information has been inputted “*=Summary!$A$4*”. This information tells the chart that the name of this sensor is located on the **Summary** worksheet in cell A4. Each series has the same information with corresponding cell number. The second box named “Values” has the information “*=Data!$A$1:$A$1400*”. This equation tells the chart to plot everything in column A from row 1 to row 1400. If there is more row data than 1400, then the user must manually go in and increase each Value from 1400 to the amount of data rows. An example of the **Alarm Rate** worksheet is shown in Figure 7.3.

Figure 7.3 Excel Alarm Rates Worksheet Illustration



Summary: This sheet is a summary of the Sensor alarms. The columns A, D, G, and J are the sensor’s names that are linked to the **Sensitivity** worksheet, which is where the user manually inputted the sensor’s name. The next columns B, E, H, and K sum up all of the alarms for each sensor in the **Data** worksheet and divide them by the total possible alarms. The total possible alarms are calculated in cell N3 with the Excel function COUNT. This function counts the number of cells that contain an actual number within an array. The actual command is ***"=COUNT(Data!A:A)",*** which counts all the numbers that exist in row A. The percentage is then calculated by dividing the total number of alarms, by the number in cell N4. This cell has been hidden from the user. Before the percentage is actually listed, an If function is used so that no Div/0 will appear for any cells that do not have a sensor name. The IF statement "*=IF(A4="","" ",IF(A4=0,"",B4/$N$3))*" will only show the percentage in the cell if there is a sensor listed in the corresponding cell. The next column is the "Average Alarm Deviation" column where the average of all the "operationally significant" alarms is calculated. Currently this list summary page will list up to 100 sensor signals. An example of the **Summary** worksheet is shown in Figure 7.4.

Figure 7.4 Excel Summary Worksheet Illustration

Operationally Significant Sensor Signal Alarm Summary														
Sensor ID Tag Number	Number of Alarms	Alarm %	Ave. Alarm Deviation	Sensor ID Tag Number	Number of Alarms	Alarm %	Ave. Alarm Deviation	Sensor ID Tag Number	Number of Alarms	Alarm %	Ave. Alarm Deviation	Sensor ID Tag Number	Number of Alarms	Alarm %
F673	1030	77.97%	23.47	P932	11	0.83%	19.38		0				0	
F674	1030	77.97%	23.50	P936	8	0.61%	20.99		0				0	
F679	900	68.13%	20.37	P937	10	0.76%	18.87		0				0	
F680	885	66.99%	20.97		0				0				0	
T476	21	1.59%	8.45		0				0				0	
T477	19	1.44%	9.36		0				0				0	
T671	17	1.29%	8.07		0				0				0	
T672	21	1.59%	6.59		0				0				0	
T719	33	2.50%	5.63		0				0				0	
T720	23	1.74%	8.05		0				0				0	
T721	15	1.14%	12.07		0				0				0	
T722	22	1.67%	8.41		0				0				0	
T728	19	1.44%	9.61		0				0				0	
T729	22	1.67%	8.33		0				0				0	
T730	24	1.82%	7.72		0				0				0	
T731	25	1.89%	7.37		0				0				0	
T780	28	2.12%	6.14		0				0				0	
T781	24	1.82%	7.12		0				0				0	
T800	37	2.80%	4.70		0				0				0	
T801	36	2.73%	4.85		0				0				0	
T820	20	1.51%	8.45		0				0				0	
T821	24	1.82%	7.08		0				0				0	
T840	46	3.48%	3.88		0				0				0	
T841	31	2.35%	5.60		0				0				0	
P931	13	0.98%	17.07		0				0				0	

Deviations: This worksheet was created to make the Average Alarm Deviation calculation possible. The worksheet multiplies the **Data** worksheet by the **Results** worksheet so that only the deviations for the "operationally significant alarms" are considered. The Excel command line is *"=ABS(Results!A1)*Data!A1"* which takes the absolute deviation from the **Results** worksheet multiplied by the **Data** worksheet which is either a 0 for an "insignificant operational" alarm or a 1 for an "operationally significant" alarm.

7.3 Results.xls Program

This program is a simplified version of the **Deviations.xls** program. It contains the worksheets **Data, Alarm Rates,** and **Summary**. The only file that is inputted into this program is the one of the MSET output files, which is inputted into the **Data** worksheet. This program is a lot smaller and much faster than the **Deviations.xls** program. It is recommended to evaluate MSET alarms and when the MSET sensitivity is not that important.

When opening this program, a question will pop asking the user "The workbook you opened contains automatic links to information in another workbook. Do you want to update this work with changes made to the other workbook? Yes or No". This Excel program contains links to the **Sensor.xls** program. This link is just the names of the sensor signals that have been inputted into MSET. If the order of these sensor signals have not changed from the last time the **Sensor.xls** program was used or this program than it is not necessary to update the links. If the order of the sensor signals has changed, then the link must be updated. It is also possible to manually input these signals' names into the columns "Sensor's Id Tag Number".

After the selection has been made, the workbook will open and the MSET output file can be inputted into the worksheet **Data**. To obtain the proper data, open up the MSET file and find the data files that say "Sen_Stat.XXX". The XXX can either be .BART, .SSA, .PSEM, .VPR, or .VSET. It is recommended to using the Sen_Stat.SSA. Open up this MSET output file, then select all and copy. Now go to the **Data** worksheet. Before you paste the Sen_Stat information into this page make sure it is complete empty by clicking on the upper left hand corner to select all and hitting the **Delete Key**. [**DO NOT** right click the mouse key and hit "deleted".] Once you are sure the worksheet is empty, paste the Sen_Stat information into the page by clicking cell A1 and then selecting paste. Now the information will all be in column A. Highlight column A, open the Data file at the top of the page, then click on the "Text to Columns", and finally click the "Next >" button followed by the "Final" button.

Now the data is in the correct columns and the user can then click on either the **Alarm Rates** worksheet or the **Summary** worksheet. The **Alarm Rates** is an area chart that shows where the alarm occurs. If multiple alarms occur at the same location then they will pile on top of each other. To determine what sensor the alarm is, just place the mouse over the alarm and a dialogue box will appear with the name of the sensor.

8. Observed Results of Applying the 28-Sensor Model

8.1 Introduction

Previous sections have discussed different aspects of applying MSET to monitor the performance of DB heat balance sensor signals, including pre-processing, parameter values, alarm sensitivities, data set doubling, post-processing, and two different MSET models. These investigations gave insight into MSET performance and improved the MSET user interfaces. To have real value, the usefulness of the results should be demonstrated by an extended application to monitoring the Davis-Besse heat balance sensor signals performance. The techniques, which yield the best results with regards to sensor alarm monitoring, should be determined in order to make this research useful. This section explains how each technique effects MSET performance and will also provide the recommended parameter settings. The topics discussed include the pre-processing program **Sensor.xls**, the post-processing program **Deviation.xls** or **Results.xls**, double or single data sets, and recommend values for the MSET parameters disturbance magnitude (DM), False Alarm Probability (FA), and Missed Alarm Probability (MA). The MSET parameter values are important because they affect the MSET alarm sensitivity. From the standpoint of monitoring the heat balance input signal performance, it is desirable to have the MSET alarm sensitivity levels coincide with what Davis-Besse Engineers regard as the level of “operationally significant deviations” in a signal’s observed mean value at the time the training data set was recorded. Based on the experience of DB engineers the operationally significant deviation levels for the heat balance signals are: 0.1% for feed water flow, 0.2 °F for temperatures, and 15 PSI for pressures (Reference 10).

Several attempts were made to make the MSET alarm sensitivity levels correspond at least approximately to the foregoing values. In some cases these efforts were somewhat successful, but for other signals the MSET alarm level was significantly below what DB Engineers regard as operationally significant – thus creating the potential for the occurrence of a significant number of “operationally insignificant” MSET alarms. The **Deviation.xls** program eliminates alarms of this type.

To determine which MSET parameters settings are most suitable for monitoring Davis-Besse heat balance signals, several tests were performed. A percentage deviation was inserted into both the single and double data sets. The deviations were inserted both by a step process and a gradual process to determine how these deviation insertions affected MSET alarm sensitivity. The deviation insertions started at 2.0%, decreased to 1.0%, followed by 0.9%, 0.8%, …, 0.1%, 0.09%, 0.08%, …, 0.01%. These alarm insertions lasted for 20 data points. For the gradual insertion, the previous nine data points before the 20 constant deviation data points were increased by equal fractional deviations so that the deviation increase was gradual.

8.2 Pre-processing: Sensor.xls

The pre-processing program **Sensor.xls** is not a major factor in determining whether or not a heat-balance sensor signal is failing or not. As results of this research and prior investigations, the important sensor signals have been determined and placed in a 28-sensor MSET model. The program **Sensor.xls** is a general-purpose program that is most useful when the components of a new MSET model are being identified. However, this program can determine the amount of correlation between the sensor signals in the MSET 28-sensor heat balanced model and these correlations may provide insight as to why some signals are more likely to fail than others. Another function of the program is to ensure that the input data set is complete. Some data set files have had one or more blank rows in them. The **Check** worksheet function in the program identifies blank rows so that the data file can be repaired.

8.3 Post-processing: Deviation.xls or Results.xls

The post-processing programs are more useful in determining the performance of the 28-sensor model signals. Either one of the two programs, **Deviation.xls** or **Results.xls**, simplifies the process of determining sensor signal performance. These programs identify which sensor is producing alarms, when the alarms occur, and the alarm percentage. More information on these programs is provided in Section 7.

8.4 Double or Single Data Sets

Doubling the data set file was first considered as a way to balance out the distributions of sensor signals T885 and T901. Once these sensor signals were eliminated from the model, the main purpose of data set doubling was eliminated. However, an investigation was done to determine which of the two processes produced better MSET alarm sensitivity with regards to the desired cutoff values.

The double data experiments were set up with two different cases. The first case was to model the single data experiment and a double May 30 data against another double May 30 data. These experiments were run with varied DM, FA, and MA. The results can be seen in **Tables 8.1 - 8.3**. In general, the double data set experiments were less alarm sensitive than their single data set companions. However, the magnitude of variation in the MSET alarm sensitivity was not as large as expected. The largest increases were for the temperature signal sensitivities, while the pressure signal and flow signal sensitivities stayed about the same. The most unexplained variation was for T476, which had a sensitivity of 0.05% for the single data, but had a sensitivity of 1.0% for the double data set. The loss of T476 alarm sensitivity was unexpected, but it was present in all of the DM, FA, and MA experiments.

The second experimental case that was performed was to use an actual MSET training data set to observe how the alarm sensitivity behaved with actual test data set. The results at reported in Tables 8.4 - 8.6. The training data of June 5 combined with June 12 was used because it showed fewer MSET alarms than the other combined training data. The test data was chosen to be the doubled May 30 data to keep a constant in the experiment. The results of these experiments were similar to the previous experiment although some signal alarms became more sensitive. The T476 alarm sensitivity, in particular became higher, going from it previous double data set value of 1.0% to the nominal single data set value of 0.04%

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The double data set experiments did not generally show significant enough changes in the MSET alarm sensitivity to warrant routine use of the technique. Further, when double data sets are inputted into the post-processing programs, especially **Deviations.xls**, the program runs 2x to 3x slower. These results lead to the decision to drop the data doubling set techniques as a worthwhile signal performance monitoring method.

8.5 Disturbance Magnitude (DM)

The DM experiments were performed with values of 3, 5, 7, and 10. Both the FA and the MA were kept constant at 0.001 as the DM was varied. Both the single data and the double data set signal sensitivity level results are shown in Table 8.1 using the May 30 data set for both training and testing. Table 8.4 shows similar results using May 22 for the training data set and May 30 for the test data set. Table 8.1 shows two single data cases; the first case for step deviation sensitivities and the second case for the gradually increasing deviations of the same total magnitude as for the step case. For the most part no significant differences can be found between a gradual increasing deviation and a step deviation. Therefore in Table 8.4 only the results for a step deviation are shown.

The alarm sensitivity variations were not particularly significant as the DM was increased. For the flow sensor signals the MSET alarm sensitivity was 0.40% for a DM of 3 and increased to 0.50% when the DM was increased to 10. The pressure sensor signals showed a wider variety of sensitivity levels, but again as the DM was increased the changes in the sensitivities were small, if any. The temperature signals all had sensitivities ranging from 0.02% to 0.06% for a DM of 3. When the DM increased to 10, the sensitivity range were 0.04% to 0.08%, which is not particularly significant. The biggest MSET alarm sensitivity increases occurred when the DM value was increased from 3 to 5. The DM value of 3 produces the alarm sensitivities that are close to "operationally significant" cutoff levels, except for the flow. Some of the alarm sensitivity levels are a little larger than cutoff levels, but only by a hundredth of a percent, which only translates to very small temperature deviation. These deviations are small enough, so that operationally significant temperature sensor alarms will not be overlooked. For the flow sensor signals, the signal distributions are too broad obtain an MSET alarm sensitivity of less than 0.4% regardless of the DM value even though 0.1% flow deviations are regarded as operationally significant. A few operationally significant flow alarms will probably be missed because of the low MSET alarm sensitivity, but all major flow alarms should be picked-up by MSET. Hence a DM value of 3 is the best value for the MSET disturbance magnitude. This value is also consistent with conclusions reached in Reference 8. Some operationally insignificant MSET alarms [particularly for pressure signals] should be expected with this DM value, but they will be eliminated by using the post-processing program **Deviations.xls**.

8.6 False Alarm Probability (FA)

The FA experiments were performed with values of 0.001, 0.01, and 0.1. Both of the DM and MA were kept constant as the FA varied. The DM value was set to 5 and the MA value was kept at 0.001. Both the single data and the double data set alarm sensitivity results are shown in Table 8.2 for May 30 as both the training and testing data set. Table 8.5 shows similar results using the May 22 data set for training and the May 30 data set for testing.

The FA did not vary the MSET alarm sensitivity very much. Table 8.2 demonstrates that the as the FA increased from 0.001 to 0.1, it did not have a significant effect on the signal alarm sensor sensitivity. Table 8.2 also shows that only three sensor signal alarms were more sensitive when the FA was decreased from 0.001 to 0.01, while Table 8.5 shows that only two sensor signal alarms became more sensitive when the FA was increased. Both the 0.01 and 0.1 FA values only changed the overall MSET alarm sensitivity by a few hundredths of a percent for most sensor signals. However, one significant problem with the 0.1 FA value was that more pop up alarms[1] occur. The significance of these pop up alarms are that they are more likely to record as alarms for a high signal deviations that only occurs for a few data points. With a small value for FA, MSET permits high deviations for a few data points without recording an alarm. An FA value of 0.1 increases the likelihood of a small range of high deviations to produce an alarm, when an alarm is not warranted. Hence the original MSET value of 0.001 for the False Alarm Probability is the recommended for DB heat balance signal monitoring.

8.7 Missed Alarm Probability (MA)

The MA experiments were performed with MA values of 0.001, 0.01, and 0.1. Both of the DM and FA were kept constant as the FA varied. The DM value was kept constant at 5, while the FA value was kept at 0.001. Both the single data and the double data set results are shown in Table 8.3 for the training and testing data May 30, while Table 8.6 shows the result May 22 training with the May 30 testing data.

The MA parameter has more effect on the MSET alarm sensitivity than the FA parameter. Table 8.3 demonstrates that as the MA increased from 0.001 to 0.01, seven sensor signals in the model have more sensitive alarm levels and as the MA increased from 0.01 to 0.1, eighteen sensor signals have more sensitive alarm levels. In Table 8.6, eight sensor signal alarm levels became more sensitive when the MA went from 0.001 to 0.01, while nineteen sensor signal alarm levels became more sensitive when the MA went from 0.01 to 0.1. Even though the MA values of 0.1 and 0.01 make MSET alarm levels more sensitive, the recommended value for the MA is still 0.001. The 0.01 MA value only improves the overall MSET alarm sensitivity of a few sensor signals by hundredths of a percent. The 0.1 MA values improves the overall MSET alarm sensitivity of roughly half the sensor signals, but again only by a few hundredths of a percent, plus the 0.1 MA value increases the probability of pop up alarms.

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[1] Pop Up Alarms are discussed in Reference 9

Table 8.1 MSET Alarm Sensitivity with Varying DM Parameters and Same Training and Testing Data Sets[1]

		28 Sensor Single Data - May 30								28 Sensor Double Data - May 30							
	Cutoff	**Step Increase**				**Gradual Increase**				**Step Increase**				**Gradual Increase**			
Sensor	**Values**	**DM = 3**	**DM = 5**	**DM = 7**	**DM = 10**	**DM = 3**	**DM = 5**	**DM = 7**	**DM = 10**	**DM = 3**	**DM = 5**	**DM = 7**	**DM = 10**	**DM = 3**	**DM = 5**	**DM = 7**	**DM = 10**
F673	**0.10**	0.40	0.40	0.50	0.50	0.40	0.40	0.50	0.50	0.30	0.40	0.40	0.40	0.30	0.40	0.40	0.40
F674	**0.10**	0.40	0.40	0.50	0.50	0.40	0.40	0.50	0.50	0.30	0.40	0.40	0.40	0.30	0.40	0.40	0.40
F679	**0.10**	0.40	0.40	0.50	0.60	0.40	0.40	0.50	0.50	0.40	0.50	0.50	0.50	0.40	0.50	0.50	0.50
F680	**0.10**	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.50	0.40	0.50	0.50	0.50	0.40	0.40	0.40	0.40
P931	**1.69**	0.50	0.60	0.60	0.60	0.50	0.50	0.50	0.60	0.70	0.70	0.70	0.80	0.60	0.70	0.70	0.70
P932	**1.69**	0.80	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.80	0.90	1.00	1.00
P936	**1.74**	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
P937	**1.73**	0.60	0.60	0.70	0.70	0.60	0.60	0.60	0.60	0.70	0.70	0.80	0.90	0.60	0.70	0.80	0.90
T476	**0.03**	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05	1.00	1.00	1.00	2.00	1.00	2.00	2.00	2.00
T477	**0.03**	0.04	0.04	0.05	0.05	0.04	0.04	0.04	0.04	0.05	0.07	0.07	0.07	0.04	0.05	0.06	0.07
T671	**0.04**	0.05	0.07	0.07	0.07	0.05	0.07	0.07	0.07	0.09	0.12	0.12	0.12	0.09	0.12	0.12	0.12
T672	**0.04**	0.05	0.05	0.05	0.07	0.05	0.05	0.05	0.07	0.09	0.12	0.12	0.12	0.09	0.09	0.12	0.12
T719	**0.03**	0.02	0.02	0.02	0.02	0.02	0.02	0.00	0.02	0.04	0.05	0.05	0.05	0.04	0.04	0.05	0.05
T720	**0.03**	0.05	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05
T721	**0.03**	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.04	0.04	0.05	0.05
T722	**0.03**	0.02	0.04	0.04	0.04	0.02	0.04	0.04	0.04	0.05	0.07	0.09	0.09	0.05	0.06	0.07	0.07
T728	**0.03**	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.05	0.07	0.07	0.07	0.05	0.07	0.07	0.07
T729	**0.03**	0.02	0.04	0.04	0.04	0.02	0.02	0.03	0.04	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05
T730	**0.03**	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05
T731	**0.03**	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.05	0.05	0.07	0.07	0.05	0.05	0.07	0.07
T780	**0.04**	0.06	0.07	0.08	0.08	0.06	0.07	0.07	0.08	0.09	0.11	0.11	0.11	0.08	0.09	0.11	0.11
T781	**0.04**	0.06	0.07	0.08	0.08	0.06	0.08	0.08	0.08	0.09	0.11	0.11	0.11	0.09	0.11	0.11	0.11
T800	**0.04**	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.08	0.07	0.08	0.06	0.08	0.08	0.08
T801	**0.04**	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.09	0.09	0.11	0.11	0.07	0.09	9.00	0.11
T820	**0.04**	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.06	0.06	0.08	0.06	0.06	0.06	0.06
T821	**0.04**	0.04	0.06	0.06	0.06	0.04	0.06	0.06	0.06	0.06	0.08	0.08	0.08	0.06	0.08	0.08	0.08
T840	**0.04**	0.04	0.06	0.06	0.06	0.04	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.06	0.06	0.06
T841	**0.04**	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.08	0.09	0.09	0.11	0.08	0.09	0.09	0.09

[1]All values are stated as a percentage of the mean value of the signal in the testing data set

Table 8.2 MSET Alarm Sensitivity with Varying FA Parameters and Same Training and Testing Data Sets[1]

	Cutoff	28 Sensor Single Data - May 30						28 Sensor Double Data - May 30					
		Step Increase			Gradual Increase			Step Increase			Gradual Increase		
Sensor	Values	FA = 0.001	FA = 0.01	FA = 0.1	FA = 0.001	FA = 0.01	FA = 0.1	FA = 0.001	FA = 0.01	FA = 0.1	FA = 0.001	FA = 0.01	FA = 0.1
F673	**0.10**	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
F674	**0.10**	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
F679	**0.10**	0.40	0.40	0.40	0.40	0.40	0.40	0.50	0.40	0.40	0.50	0.40	0.40
F680	**0.10**	0.40	0.40	0.40	0.40	0.40	0.40	0.50	4.00	0.40	0.40	0.40	0.40
P931	**1.69**	0.60	0.50	0.50	0.50	0.50	0.40	0.70	0.70	0.70	0.70	0.70	0.60
P932	**1.69**	0.90	0.90	1.00	0.90	1.00	1.00	0.90	0.80	0.70	0.90	0.90	0.90
P936	**1.74**	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
P937	**1.73**	0.60	0.60	0.60	0.60	0.60	0.06	0.70	0.80	0.90	0.70	0.80	0.80
T476	**0.03**	0.05	0.04	0.04	0.04	0.04	0.04	1.00	1.00	1.00	2.00	1.00	2.00
T477	**0.03**	0.04	0.04	0.04	0.04	0.04	0.04	0.07	0.07	0.05	0.06	0.05	0.05
T671	**0.04**	0.07	0.07	0.07	0.07	0.07	0.07	0.12	0.12	0.12	0.12	0.12	0.12
T672	**0.04**	0.05	0.05	0.05	0.05	0.05	0.05	0.12	0.09	0.09	0.09	0.09	0.09
T719	**0.03**	0.02	0.02	0.02	0.02	0.02	0.02	0.05	0.04	0.04	0.04	0.04	0.04
T720	**0.03**	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.05	0.04	0.04
T721	**0.03**	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.04	0.04	0.04
T722	**0.03**	0.04	0.04	0.04	0.04	0.04	0.04	0.07	0.07	0.07	0.06	0.06	0.05
T728	**0.03**	0.05	0.05	0.04	0.04	0.05	0.04	0.07	0.07	0.05	0.07	0.07	0.05
T729	**0.03**	0.04	0.02	0.02	0.02	0.02	0.02	0.05	0.05	0.04	0.05	0.04	0.04
T730	**0.03**	0.05	0.05	0.04	0.04	0.05	0.04	0.05	0.06	0.05	0.05	0.05	0.04
T731	**0.03**	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
T780	**0.04**	0.07	0.07	0.06	0.06	0.06	0.06	0.11	0.09	0.09	0.09	0.09	0.08
T781	**0.04**	0.07	0.07	0.06	0.06	0.07	0.06	0.11	0.11	0.09	0.11	0.11	0.09
T800	**0.04**	0.06	0.06	0.06	0.06	0.06	0.06	0.08	0.08	0.05	0.08	0.08	0.06
T801	**0.04**	0.06	0.06	0.06	0.06	0.06	0.06	0.09	0.09	0.09	0.09	0.09	0.09
T820	**0.04**	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.05	0.05	0.06	0.06	0.06
T821	**0.04**	0.06	0.06	0.06	0.06	0.05	0.04	0.08	0.05	0.05	0.08	0.06	0.06
T840	**0.04**	0.06	0.06	0.04	0.04	0.06	0.04	0.06	0.05	0.05	0.06	0.06	0.06
T841	**0.04**	0.06	0.06	0.06	0.06	0.06	0.06	0.09	0.09	0.08	0.09	0.09	0.08

[1]All values are stated as a percentage of the mean value of the signal in the testing data set

Table 8.3 MSET Alarm Sensitivity with Varying MA Parameters and Same Training and Testing Data Sets[1]

		28 Sensor Single Data - May 30						28 Sensor Double Data - May 30					
		Step Increase			Gradual Increase			Step Increase			Gradual Increase		
Sensor	Cutoff Values	MA = 0.001	MA = 0.01	MA = 0.1	MA = 0.001	MA = 0.01	MA = 0.1	MA = 0.001	MA = 0.01	MA = 0.1	MA = 0.001	MA = 0.01	MA = 0.1
F673	**0.10**	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.30	0.40	0.40	0.30
F674	**0.10**	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.30	0.40	0.40	0.30
F679	**0.10**	0.40	0.40	0.30	0.40	0.40	0.30	0.50	0.40	0.40	0.50	0.50	0.40
F680	**0.10**	0.40	0.40	0.30	0.40	0.40	0.30	0.50	0.40	0.30	0.40	0.40	0.30
P931	**1.69**	0.60	0.50	0.50	0.50	5.00	0.40	0.70	0.70	0.60	0.70	0.60	0.50
P932	**1.69**	0.90	0.80	0.60	0.90	0.80	0.60	0.90	0.80	0.80	0.90	0.90	0.90
P936	**1.74**	1.00	1.00	0.80	1.00	1.00	0.80	1.00	1.00	0.70	1.00	1.00	0.70
P937	**1.73**	0.60	0.60	0.50	0.60	0.50	0.40	0.70	0.80	0.60	0.70	0.70	0.50
T476	**0.03**	0.05	0.04	0.04	0.05	0.04	0.04	1.00	2.00	0.70	2.00	2.00	0.70
T477	**0.03**	0.05	0.04	0.04	0.04	0.04	0.04	0.07	0.05	0.05	0.05	0.05	..04
T671	**0.04**	0.07	0.07	0.05	0.07	0.07	0.05	0.12	0.12	0.07	0.12	0.10	0.07
T672	**0.04**	0.05	0.05	0.03	0.05	0.05	0.03	0.12	0.09	0.07	0.09	0.09	0.07
T719	**0.03**	0.02	0.02	0.02	0.02	0.02	0.02	0.05	0.04	0.04	0.04	0.04	0.04
T720	**0.03**	0.05	0.05	0.04	0.05	0.05	0.04	0.05	0.05	0.04	0.05	0.05	0.04
T721	**0.03**	0.04	0.04	0.02	0.04	0.04	0.02	0.05	0.04	0.04	0.04	0.04	0.04
T722	**0.03**	0.04	0.04	0.02	0.04	0.04	0.02	0.07	0.07	0.05	0.06	0.05	0.05
T728	**0.03**	0.05	0.05	0.04	0.05	0.05	0.04	0.07	0.07	0.05	0.07	0.07	0.05
T729	**0.03**	0.04	0.02	0.02	0.02	0.02	0.02	0.05	0.04	0.04	0.05	0.04	0.04
T730	**0.03**	0.05	0.04	0.04	0.05	0.04	0.04	0.05	0.05	0.04	0.05	0.05	0.04
T731	**0.03**	0.05	0.05	0.04	0.05	0.05	0.04	0.05	0.05	0.05	0.05	0.05	0.05
T780	**0.04**	0.07	0.07	0.06	0.07	0.06	0.06	0.11	0.09	0.08	0.09	0.09	0.08
T781	**0.04**	0.07	0.06	0.04	0.08	0.06	0.04	0.11	0.11	0.09	0.11	0.11	0.09
T800	**0.04**	0.06	0.06	0.04	0.06	0.06	0.04	0.08	0.06	0.05	0.08	0.06	0.06
T801	**0.04**	0.06	0.06	0.04	0.06	0.06	0.04	0.19	0.08	0.07	0.09	0.09	0.08
T820	**0.04**	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.06	0.04	0.06	0.06	0.04
T821	**0.04**	0.06	0.06	0.04	0.06	0.04	0.04	0.08	0.06	0.06	0.08	0.06	0.06
T840	**0.04**	0.06	0.06	0.04	0.06	0.05	0.04	0.06	0.06	0.04	0.06	0.06	0.04
T841	**0.04**	0.06	0.06	0.06	0.06	0.06	0.06	0.09	0.09	0.08	0.09	0.08	0.08

[1]All values are stated as a percentage of the mean value of the signal in the testing data set

Table 8.4 MSET Alarm Sensitivity with Varying DM Parameters and Different Training and Testing Data Sets[1]

Sensor	Cutoff Values	28 Sensor Single Data - May 22 vs May 30 Step Insertion				28 Sensor Double Data - June 5/June 12 vs May 30 Step Insertion			
		DM = 3	DM = 5	DM = 7	DM = 10	DM = 3	DM = 5	DM = 7	DM = 10
F673	**0.10**	0.40	0.50	0.50	0.60	0.40	0.50	0.50	0.60
F674	**0.10**	0.40	0.50	0.50	0.60	0.40	0.50	0.50	0.50
F679	**0.10**	0.30	0.40	0.40	0.40	0.40	0.40	0.40	0.40
F680	**0.10**	0.30	0.40	0.50	0.70	0.40	0.50	0.60	0.90
P931	**1.69**	0.50	0.50	0.60	0.50	0.50	0.50	0.50	0.50
P932	**1.69**	0.70	0.80	1.00	1.00	0.70	0.70	0.60	0.70
P936	**1.74**	1.00	1.00	1.00	1.00	0.70	1.00	1.00	1.00
P937	**1.73**	0.90	1.00	0.90	0.90	0.60	0.60	0.70	0.70
T476	**0.03**	----	0.04	0.04	0.04	0.04	0.04	0.04	0.05
T477	**0.03**	0.04	0.04	0.04	0.04	0.02	0.04	0.04	0.04
T671	**0.04**	0.05	0.07	0.07	0.07	0.07	0.07	0.07	0.07
T672	**0.04**	0.05	0.05	0.05	0.07	0.05	0.07	0.07	0.07
T719	**0.03**	0.02	0.04	0.04	0.04	0.02	0.02	0.02	0.02
T720	**0.03**	0.05	0.07	0.07	0.07	0.04	0.05	0.05	0.05
T721	**0.03**	0.04	0.05	0.05	0.05	0.04	0.04	0.05	0.05
T722	**0.03**	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05
T728	**0.03**	0.05	0.07	0.07	0.07	0.04	0.05	0.05	0.05
T729	**0.03**	0.02	0.04	0.04	0.04	0.04	0.04	0.04	0.04
T730	**0.03**	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05
T731	**0.03**	0.05	0.07	0.07	0.07	0.05	0.05	0.05	0.05
T780	**0.04**	0.06	0.08	0.08	0.08	0.04	0.06	0.06	0.06
T781	**0.04**	0.06	0.08	0.08	0.09	0.06	0.08	0.08	0.08
T800	**0.04**	0.06	0.06	0.06	0.06	0.04	0.06	0.06	0.06
T801	**0.04**	0.08	0.09	0.09	0.09	0.08	0.09	0.09	0.09
T820	**0.04**	0.04	0.06	0.06	0.06	0.04	0.06	0.06	0.06
T821	**0.04**	0.06	0.08	0.08	0.08	0.04	0.06	0.06	0.06
T840	**0.04**	0.04	0.04	0.04	0.06	0.04	0.04	0.06	0.06
T841	**0.04**	0.04	0.04	0.04	0.06	0.06	0.06	0.08	0.08

[1]All values are stated as a percentage of the mean value of the signal in the testing data set

Table 8.5 MSET Alarm Sensitivity with Varying FA Parameters and Different Training and Testing Data Sets[1]

Sensor	Cutoff Values	Single Data - May 22 vs May 30 Step Insertion FA = 0.001	FA = 0.01	FA = 0.1	Double Data - June 5/June 12 vs May 30 Step Insertion FA = 0.001	FA = 0.01	FA = 0.1
F673	**0.10**	0.50	0.50	0.40	0.50	0.50	0.50
F674	**0.10**	0.50	0.50	0.40	0.50	0.50	0.50
F679	**0.10**	0.40	0.40	0.40	0.40	0.40	0.40
F680	**0.10**	0.40	0.40	0.40	0.50	0.50	0.50
P931	**1.69**	0.50	0.50	0.50	0.50	0.60	0.50
P932	**1.69**	0.80	1.00	1.00	0.70	0.70	0.70
P936	**1.74**	1.00	1.00	1.00	1.00	0.70	0.70
P937	**1.73**	1.00	0.80	0.80	0.60	0.70	0.60
T476	**0.03**	0.04	0.04	0.02	0.04	0.04	0.04
T477	**0.03**	0.04	0.04	0.04	0.04	0.04	0.02
T671	**0.04**	0.07	0.07	0.07	0.07	0.07	0.07
T672	**0.04**	0.05	0.05	0.05	0.07	0.07	0.05
T719	**0.03**	0.04	0.04	0.02	0.02	0.02	0.02
T720	**0.03**	0.07	0.07	0.05	0.05	0.05	0.04
T721	**0.03**	0.05	0.05	0.04	0.04	0.04	0.04
T722	**0.03**	0.05	0.05	0.04	0.05	0.05	0.05
T728	**0.03**	0.07	0.07	0.05	0.05	0.05	0.04
T729	**0.03**	0.04	0.04	0.02	0.04	0.04	0.02
T730	**0.03**	0.05	0.04	0.04	0.05	0.05	0.05
T731	**0.03**	0.07	0.07	0.05	0.05	0.05	0.04
T780	**0.04**	0.08	0.08	0.06	0.06	0.06	0.06
T781	**0.04**	0.08	0.08	0.06	0.08	0.08	0.06
T800	**0.04**	0.06	0.06	0.06	0.06	0.06	0.04
T801	**0.04**	0.09	0.09	0.08	0.09	0.09	0.08
T820	**0.04**	0.06	0.06	0.04	0.06	0.06	0.04
T821	**0.04**	0.08	0.08	0.06	0.06	0.06	0.04
T840	**0.04**	0.04	0.04	0.04	0.04	0.04	0.04
T841	**0.04**	0.04	0.04	0.04	0.06	0.06	0.06

[1]All values are stated as a percentage of the mean value of the signal in the testing data set

Table 8.6 MSET Alarm Sensitivity with Varying MA Parameters and Different Training and Testing Data Sets[1]

Sensor	Cutoff Values	Single Data - May 22 vs May 30 Step Insertion MA = 0.001	Single Data - May 22 vs May 30 Step Insertion MA = 0.01	Single Data - May 22 vs May 30 Step Insertion MA = 0.1	Double Data - June 5/June 12 vs May 30 Step Insertion MA = 0.001	Double Data - June 5/June 12 vs May 30 Step Insertion MA = 0.01	Double Data - June 5/June 12 vs May 30 Step Insertion MA = 0.1
F673	**0.10**	0.50	0.50	0.30	0.50	0.50	0.40
F674	**0.10**	0.50	0.50	0.30	0.50	0.50	0.40
F679	**0.10**	0.40	0.40	0.30	0.40	0.40	0.30
F680	**0.10**	0.40	0.40	0.30	0.50	0.40	0.30
P931	**1.69**	0.50	0.50	0.40	0.50	0.50	0.40
P932	**1.69**	0.80	0.80	0.60	0.70	0.60	0.60
P936	**1.74**	1.00	1.00	1.00	1.00	0.70	0.60
P937	**1.73**	1.00	0.90	0.70	0.60	0.60	0.50
T476	**0.03**	0.04	0.02	----	0.04	0.04	0.04
T477	**0.03**	0.04	0.04	0.02	0.04	0.04	0.02
T671	**0.04**	0.07	0.07	0.05	0.07	0.07	0.05
T672	**0.04**	0.05	0.05	0.03	0.07	0.07	0.05
T719	**0.03**	0.04	0.02	0.02	0.02	0.02	0.02
T720	**0.03**	0.07	0.05	0.05	0.05	0.05	0.04
T721	**0.03**	0.05	0.04	0.04	0.04	0.04	0.02
T722	**0.03**	0.05	0.04	0.04	0.05	0.05	0.04
T728	**0.03**	0.07	0.07	0.05	0.05	0.05	0.04
T729	**0.03**	0.04	0.04	0.02	0.04	0.04	0.02
T730	**0.03**	0.05	0.04	0.04	0.05	0.05	0.04
T731	**0.03**	0.07	0.07	0.05	0.05	0.06	0.04
T780	**0.04**	0.08	0.06	0.06	0.06	0.06	0.04
T781	**0.04**	0.08	0.08	0.06	0.08	0.06	0.06
T800	**0.04**	0.06	0.06	0.04	0.06	0.06	0.04
T801	**0.04**	0.09	0.09	0.08	0.09	0.09	0.08
T820	**0.04**	0.06	0.06	0.04	0.06	0.06	0.04
T821	**0.04**	0.08	0.08	0.06	0.06	0.06	0.04
T840	**0.04**	0.04	0.04	0.02	0.04	0.04	0.04
T841	**0.04**	0.04	0.04	0.04	0.06	0.06	0.06

[1]All values are stated as a percentage of the mean value of the signal in the testing data set

8.8 Application of Post-Processing Programs to Davis-Besse Data Sets

Figures 8.1 through 8.6 demonstrate how the post-processing programs work with representative Davis-Besse data sets. Two different MSET single data set files were chosen to demonstrate the characteristics of each post-processing program. The figures display charts and summaries from both the **Results.xls** and **Deviation.xls** programs. These figures demonstrate the differences of each program and how they process the data in a MSET output file for an ordinary 28-Sensor Model Davis-Besse data set.

The first set of figures show the results for the May 22 training data set with June 26 testing data set. Figure 8.1 is the **Results.xls** program alarm chart. The chart shows an alarm for two sensor signals T477 (pink) and P932 (blue). The summary table, Figure 8.2, shows that sensor signal T477 has 381 alarms and P932 has 1306 alarms. The next two figures are for the same training and testing data sets, but after the MSET results were processed by the **Deviation.xls** program. Figure 8.3 shows that the "Alarm Chart" no longer has any alarms for P932 and only a few alarms for T477. The summary table in Figure 8.4 shows that no alarms exist for P932 and 132 alarms for T477. This demonstration shows that even though MSET found alarms for P932, the alarms were below the operationally significant level and were eliminated by the **Deviations.xls** program.

The second set of figures show the results for the May 22 training data with July 24 testing data set. This MSET run was the last one performed as part of this project and along with the evidence of T477 signal histogram, led to the conclusion that T477 is drifting into an "operationally significant" alarm state. Figure 8.5 demonstrates the MSET output data in the **Results.xls** program. The figure shows T477 (pink) as a constant alarm, T721 (yellow) as a minute alarm, and T671 (blue) as an alarm late in the test time frame. The summary Figure 8.6 shows that T477 has 1318 alarms out of a possible 1322, T721 has only 7 alarms, and T671 has 160 alarms. When this same MSET output data was processed by the **Deviations.xls** program, the results were similar. Figure 8.7 shows all three sensor signals producing alarms, even though the alarms are no longer constant. The T477 alarm (pink) is present from the beginning to the end, T721 (yellow) is an even smaller alarm than before, and T671 (blue) is present but not constant. The summary table, Figure 8.8, shows that T477 has 1069 alarms, T721 only has 3 alarms, and T671 has 72 alarms. The T477 drift is still dominantly present even after some of the insignificant alarms are eliminated from these figures, which demonstrate that the **Deviation.xls** program eliminates any alarm that is not operationally significant and retains all other alarms.

These figures demonstrate the effectiveness of the post-processing programs, particularly the **Deviations.xls** program. The program examined the P932 MSET alarms and because they were not operationally significant, these alarms were eliminated. In the second MSET run, the program eliminated only a few of the alarms, because T477 signal has started to drift out of calibration at an operationally significant level.

Figure 8.1 Results.xls Chart of May 22 Train and June 26 Test

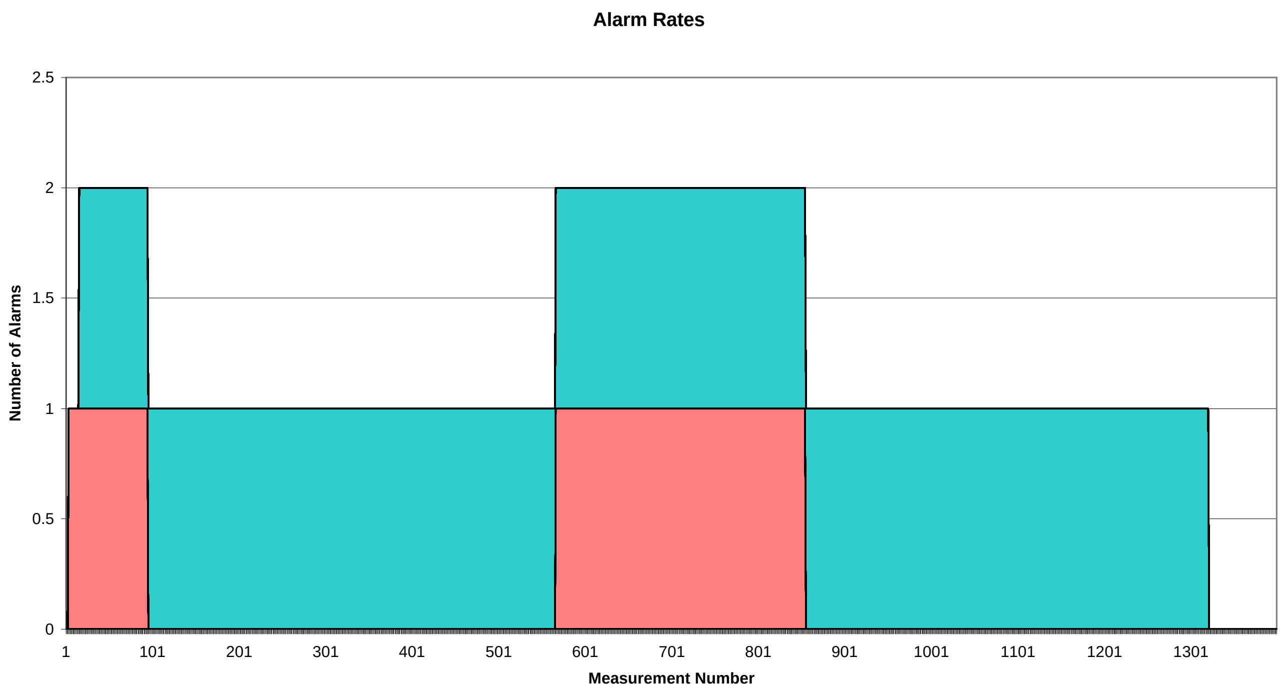

Figure 8.2 Results.xls Summary of May 22 Train and June 26 Test

MSET Sensor Signal Alarm Summary											
Sensor ID Tag Number	Number of Alarms	Alarm %	Sensor ID Tag Number	Number of Alarms	Alarm %	Sensor ID Tag Number	Number of Alarms	Alarm %	Sensor ID Tag Number	Number of Alarms	Alarm %
F673	0	0.000%	P932	1306	98.864%		0			0	
F674	0	0.000%	P936	0	0.000%		0			0	
F679	0	0.000%	P937	0	0.000%		0			0	
F680	0	0.000%		0			0			0	
T476	0	0.000%		0			0			0	
T477	381	28.842%		0			0			0	
T671	0	0.000%		0			0			0	
T672	0	0.000%		0			0			0	
T719	0	0.000%		0			0			0	
T720	0	0.000%		0			0			0	
T721	0	0.000%		0			0			0	
T722	0	0.000%		0			0			0	
T728	0	0.000%		0			0			0	
T729	0	0.000%		0			0			0	
T730	0	0.000%		0			0			0	
T731	0	0.000%		0			0			0	
T780	0	0.000%		0			0			0	
T781	0	0.000%		0			0			0	
T800	0	0.000%		0			0			0	
T801	0	0.000%		0			0			0	
T820	0	0.000%		0			0			0	
T821	0	0.000%		0			0			0	
T840	0	0.000%		0			0			0	
T841	0	0.000%		0			0			0	
P931	0	0.000%		0			0			0	

Figure 8.3 Deviations.xls Chart of May 22 Train and June 26 Test

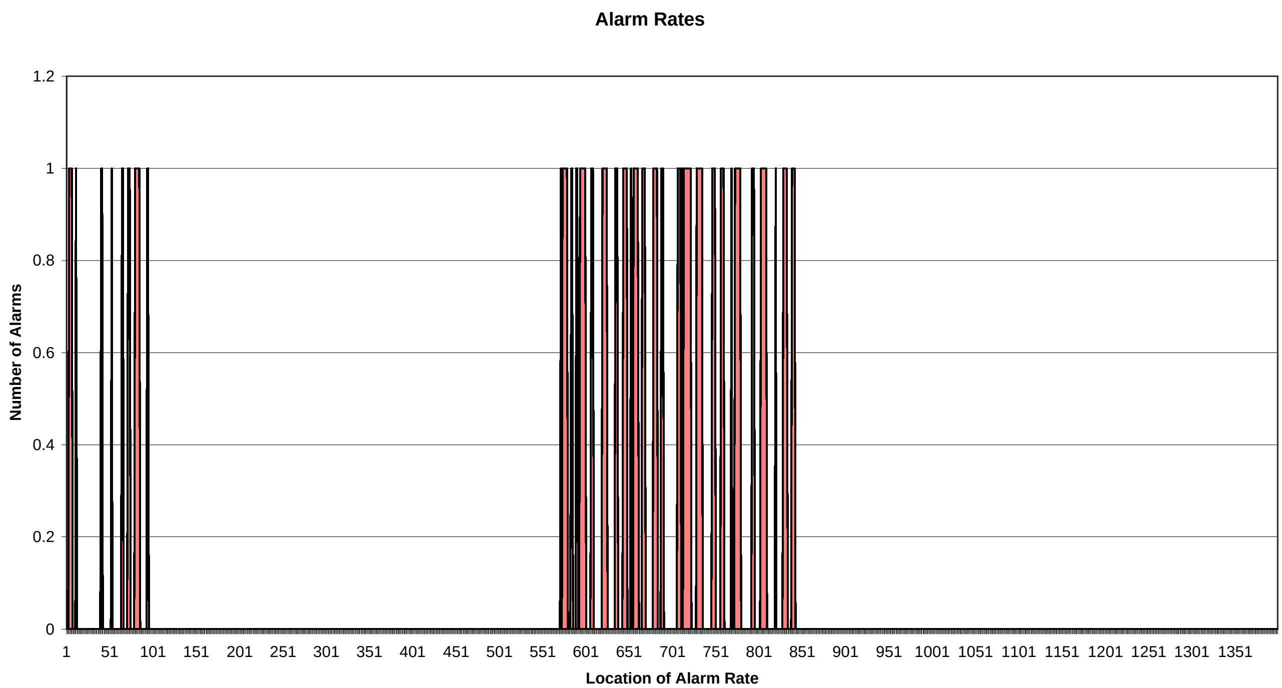

Figure 8.4 Deviations.xls Summary of May 22 Train and June 26 Test

Operationally Significant Sensor Signal Alarm Summary

Sensor ID Tag Number	Number of Alarms	Alarm %	Ave. Alarm Deviation	Sensor ID Tag Number	Number of Alarms	Alarm %	Ave. Alarm Deviation	Sensor ID Tag Number	Number of Alarms	Alarm %	Ave. Alarm Deviation	Sensor ID Tag Number	Number of Alarms	Alarm %
F673	0	0.00%		P932	0	0.00%			0				0	
F674	0	0.00%		P936	0	0.00%			0				0	
F679	0	0.00%		P937	0	0.00%			0				0	
F680	0	0.00%			0				0				0	
T476	0	0.00%			0				0				0	
T477	132	9.99%	0.25		0				0				0	
T671	0	0.00%			0				0				0	
T672	0	0.00%			0				0				0	
T719	0	0.00%			0				0				0	
T720	0	0.00%			0				0				0	
T721	0	0.00%			0				0				0	
T722	0	0.00%			0				0				0	
T728	0	0.00%			0				0				0	
T729	0	0.00%			0				0				0	
T730	0	0.00%			0				0				0	
T731	0	0.00%			0				0				0	
T780	0	0.00%			0				0				0	
T781	0	0.00%			0				0				0	
T800	0	0.00%			0				0				0	
T801	0	0.00%			0				0				0	
T820	0	0.00%			0				0				0	
T821	0	0.00%			0				0				0	
T840	0	0.00%			0				0				0	
T841	0	0.00%			0				0				0	
P931	0	0.00%			0				0				0	

Figure 8.5 Results.xls Chart of May 22 Train and July 24 Test

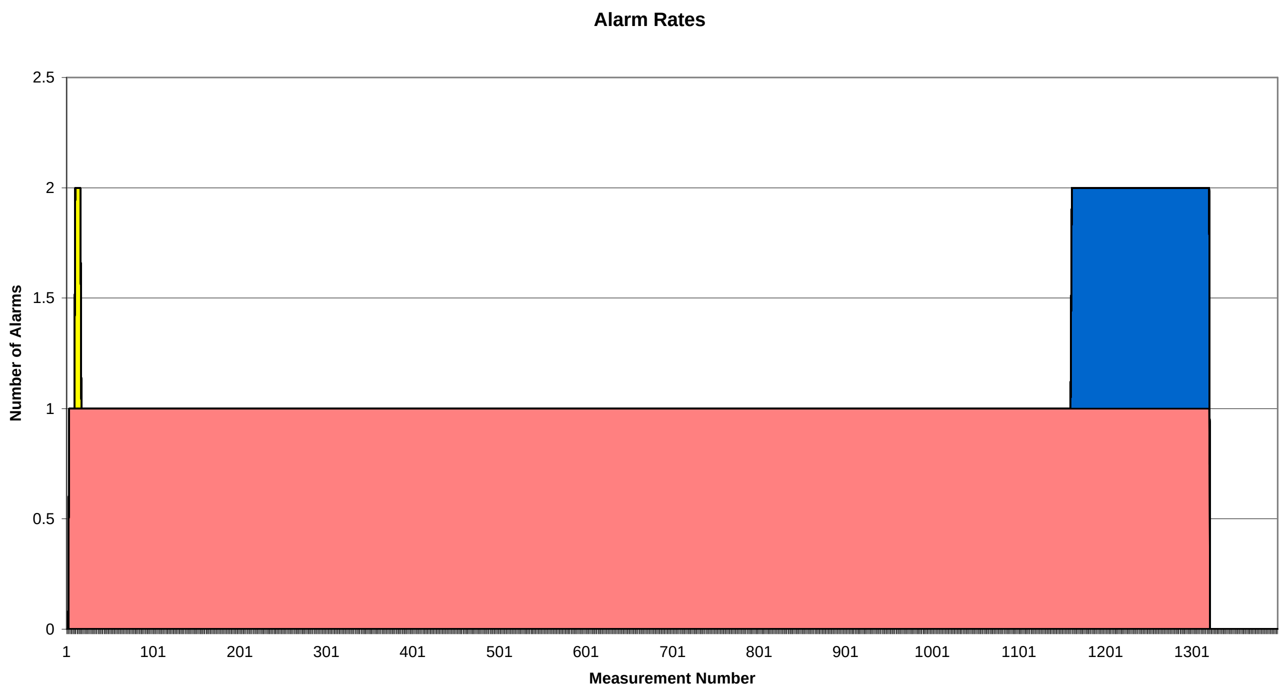

Figure 8.6 Results.xls Summary of May 22 Train and July 24 Test

MSET Sensor Signal Alarm Summary											
Sensor ID Tag Number	Number of Alarms	Alarm %	Sensor ID Tag Number	Number of Alarms	Alarm %	Sensor ID Tag Number	Number of Alarms	Alarm %	Sensor ID Tag Number	Number of Alarms	Alarm %
F673	0	0.000%	P932	0	0.000%		0			0	
F674	0	0.000%	P936	0	0.000%		0			0	
F679	0	0.000%	P937	0	0.000%		0			0	
F680	0	0.000%		0			0			0	
T476	0	0.000%		0			0			0	
T477	1318	99.773%		0			0			0	
T671	160	12.112%		0			0			0	
T672	0	0.000%		0			0			0	
T719	0	0.000%		0			0			0	
T720	0	0.000%		0			0			0	
T721	7	0.530%		0			0			0	
T722	0	0.000%		0			0			0	
T728	0	0.000%		0			0			0	
T729	0	0.000%		0			0			0	
T730	0	0.000%		0			0			0	
T731	0	0.000%		0			0			0	
T780	0	0.000%		0			0			0	
T781	0	0.000%		0			0			0	
T800	0	0.000%		0			0			0	
T801	0	0.000%		0			0			0	
T820	0	0.000%		0			0			0	
T821	0	0.000%		0			0			0	
T840	0	0.000%		0			0			0	
T841	0	0.000%		0			0			0	
P931	0	0.000%		0			0			0	

Figure 8.7 Deviations.xls Chart of May 22 Train and July 26 Test

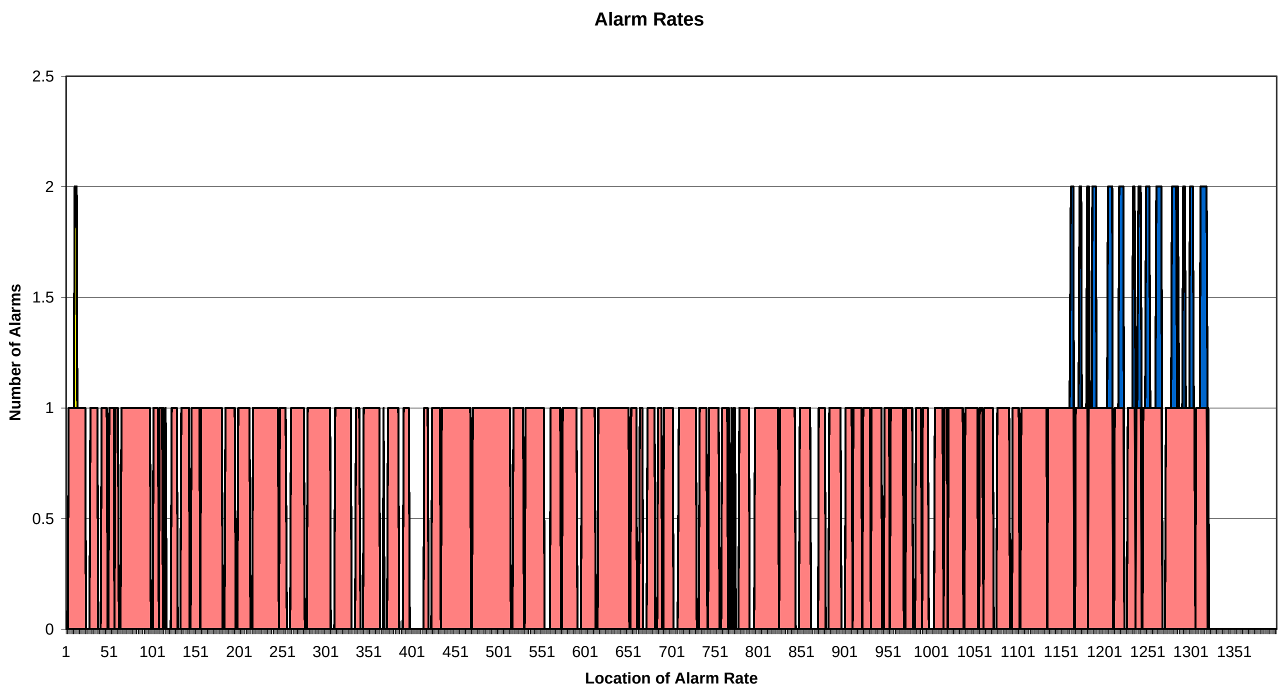

Figure 8.8 Deviations.xls Summary of May 22 Train and July 26 Test

Operationally Significant Sensor Signal Alarm Summary														
Sensor ID Tag Number	Number of Alarms	Alarm %	Ave. Alarm Deviation	Sensor ID Tag Number	Number of Alarms	Alarm %	Ave. Alarm Deviation	Sensor ID Tag Number	Number of Alarms	Alarm %	Ave. Alarm Deviation	Sensor ID Tag Number	Number of Alarms	Alarm %
F673	0	0.00%		P932	0	0.00%			0				0	
F674	0	0.00%		P936	0	0.00%			0				0	
F679	0	0.00%		P937	0	0.00%			0				0	
F680	0	0.00%			0				0				0	
T476	0	0.00%			0				0				0	
T477	1069	80.92%	0.35		0				0				0	
T671	72	5.45%	0.40		0				0				0	
T672	0	0.00%			0				0				0	
T719	0	0.00%			0				0				0	
T720	0	0.00%			0				0				0	
T721	3	0.23%	0.34		0				0				0	
T722	0	0.00%			0				0				0	
T728	0	0.00%			0				0				0	
T729	0	0.00%			0				0				0	
T730	0	0.00%			0				0				0	
T731	0	0.00%			0				0				0	
T780	0	0.00%			0				0				0	
T781	0	0.00%			0				0				0	
T800	0	0.00%			0				0				0	
T801	0	0.00%			0				0				0	
T820	0	0.00%			0				0				0	
T821	0	0.00%			0				0				0	
T840	0	0.00%			0				0				0	
T841	0	0.00%			0				0				0	
P931	0	0.00%			0				0				0	

9. Conclusions

The overall purpose of this research project was to make the MSET program and models more useful for monitoring the performance of the input signals used in the DBNPS heat balance calculations. The second phase of the research focused on furthering the work done in the MS project by Dagos Nica and advancing the entire MSET methodology so it can be easily used by DBNPS engineers and instrumentation specialists. During Phase 2 research was performed in four different areas: pre-processing, actual MSET alarm sensitivity, post-processing, and DPNPS signal performance monitoring.

The pre-processing stage used an Excel program to simplify all of the hand calculations that were previously necessary to determine the important sensors for an MSET model. The program uses the Excel function CORREL to determine the sensor signals that are closely correlated with the essential sensors for the MSET model. These closely correlated sensors are saved into a data file that is easily inputted into MSET. The program includes other functions such as the correlation ranking of the sensor signals, the correlation percentage of the sensor signals, a review of the data to ensure that the data file is complete.

Determining the MSET alarm sensitivity was a very complicated process. Two sensor signals were at first identified in the sensitivity experiments as being the source of extensive MSET alarms signals; T885 and T901 signals. Further research into these two sensor signals determined that they did not behave like the other sensor signals. The T885 and T901 signal histograms showed that each week's signal distribution could be very different than the previous weeks. In fact, some weeks had two main distribution points, while others weeks had three. Even the weeks with three distribution points did not behave similarly. The erratic behavior distributions were the main reasons why these sensors were eliminated from the 30-sensor model, thus leading to the creation of the 28-sensor model.

The sensor signal histograms also gave insight into the behavior of the T477 signals, which started giving MSET alarms for both July the 17 and July 24 data sets. Both the MSET alarms and the July 17 and July 24 distributions prove that the sensor T477 is failing. T477 distributions started drifting slowly, but gradually became a full failure.

Further insight into MSET alarm sensitivity was acquired by examining the MSET parameters disturbance magnitude (DM), false alarm probability (FA), and missed alarm probability (MA). The numerical sensitivity experiments were designed to observe the effects of these values on the MSET sensitivity level. The recommended DM value is 3, the FA value is 0.001, and the MA value is 0.001. These values drive the MSET sensitivity values as close to the cutoff values with out producing numerous pop-up alarms. Along with these MSET values other recommendations are to use single data sets instead of double data sets. The single data set produce a higher sensitivity, while also being smaller making it easier for the **Deviations.xls** program to complete its calculations because of their smaller size.

The post-processing programs take the MSET outputs files and output a chart and table that are user friendly. The chart shows what sensors are having errors and where these errors exist. The summary table sums up the sensor's errors and gives an error percentage for that sensor. The program **Deviations.xls** takes this function a step further and allows inputted sensor deviation to eliminate any operationally insignificant alarms that are below this deviation. This added feature allows all operationally insignificant alarms to be eliminated. The post-processing is the key program that eliminates all the operationally insignificant alarms that may occur.

The project results have significantly increased the utility of the MSET methodology for nuclear power plant applications. The project has produced a significantly more “user-friendlier” interface that makes it possible for DBNPS engineers and instrumentation specialists to easily identify when a sensor signal is deviating from a calibrated value at an operational significant level.

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